

# A review of soft computing application in mineral resources engineering

**L E Widodo**

Research Group on Earth Resources Exploration,  
Faculty of Mining and Petroleum Engineering, Bandung Institute of Technology,  
Bandung, Indonesia

\*corresponding author: [lew@mining.itb.ac.id](mailto:lew@mining.itb.ac.id)

**Abstract.** Soft Computing (SC) has played an important role with its automatic capability in complex new applications. In this paper a brief explanation of the advantages of SC will be given, namely tolerance to uncertainty, inaccuracy, approximate reasoning and partial truth supporting Machine Intelligence Quotient (MIQ) to achieve low cost solutions and better collaboration with conventional Hard Computing-based techniques (HC). Next was given insight insight into the four main branches of SC. Related to the SC application, review will be given to the SC application in mineral resources engineering, especially in mining engineering.

**Keywords:** Artificial Intelligence, Soft Computing, Neural Network, Fuzzy Logic, Evolutionary Computing, Hybrid Computing, Mining Engineering

## 1. Introduction

Artificial Intelligence (AI) or Computing Intelligence (CI), which was born due to the invention of Artificial Neural Network (ANN or NN) by McCulloch and Pitts [1] is one of the branches of computing techniques that is developing very fast today. It was called Soft Computing (SC) by Zadeh. The SC design mimics human intelligence that is applied in computing techniques with complex and sophisticated reasoning that cannot be performed by conventional computing techniques. With the existence of SC, computing techniques with Machine Intelligence (MI) currently can be divided into three main groups, namely: Hard Computing (HC); SC and Hybrid Computing (HyC), each with very characteristic features. HC is also known as a deterministic method based on mathematical techniques, such as symbolic manipulation, crisp system, binary logic and numerical analysis. The characteristic of HC is to produce a single output with precision. Uncertainty analysis for precision HC requires special techniques, which are not simple. HC is easily modeled mathematically but requires a model with precision, rigorous or rigid, sequential, machine-language and often requires a lot of computing time.

SC consists of several computing techniques and branches that are still developing, with new ideas emerging inspired by biological phenomena, human brain activity, natural law and animal behavior. These computing techniques have proven efficient in solving various complex problems. SC acts as an umbrella for computing techniques, in which the following computing techniques are grouped: (1) Fuzzy System (FS) and Probabilistic Reasoning (PR); (2) NN and (3) Evolutionary Computing (EC). Unlike the rigid and machine-language HC, SC is flexible and linguistic close to human language. In addition, SC produces imprecision solutions, so that uncertainty can be treated easily. Because it is designed to mimic human intelligence, the SC has the ability to learn, so that it can recognize the



structure of the problems faced and solve them effectively. HyC is a combination of HC and SC that inherits the advantages and disadvantages of both. This combination is used to obtain the strengths of both computing techniques and at the same time overcome their limitations. The main groups of computing techniques and derivatives are illustrated by **Figure 1**.

This paper provides a brief description of SC and also an overview of its application in mineral resources engineering focusing on mining engineering. This is necessary because SC applications tend to increase massively due to several advantages compared to HC in certain fields.

## **2. Soft Computing Techniques**

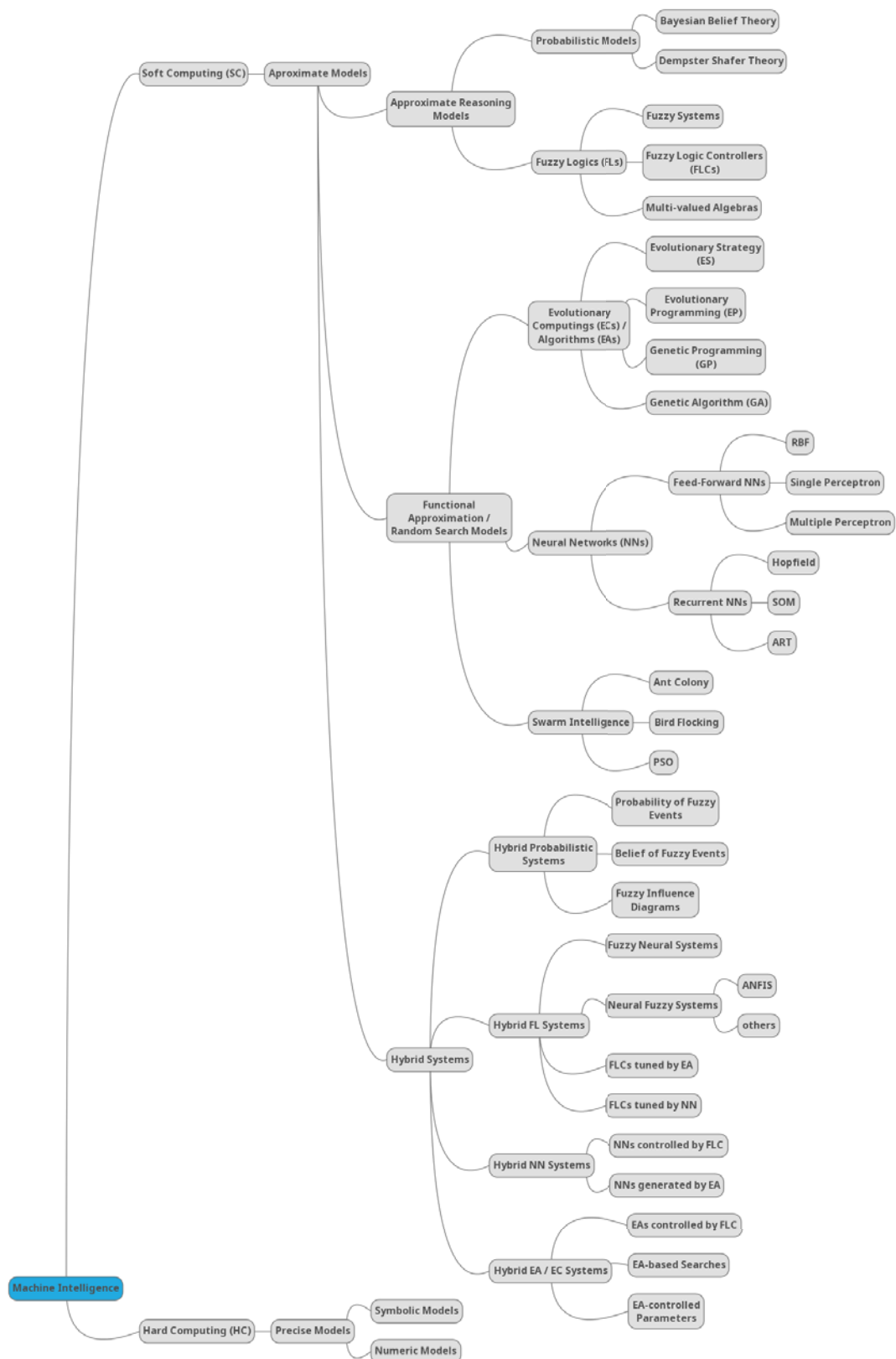
### *2.1. Approximate Reasoning*

Probabilistic Reasoning (PR) is the most suitable computing technique for analyzing and dealing with uncertainty, so that PR can be considered as an analogy to fuzzy reasoning by considering the uncertainty with the associated concept of approach. Zadeh as the first developed the concept of Fuzzy Logic (FL) [2], which mimics human reasoning in expressing information through the use of value membership. FL has the ability to handle complex decisions with linguistic approaches and logical operations but achieve extraordinary results. FL, Fuzzy System (FS), Fuzzy Inference System (FIS) are relatively inexpensive because in many cases training is usually not needed. FS mimics human actions in making human decisions by using knowledge about the target system without having to know the components of the problem model. FS can well adopt knowledge and opinion of experts, which can be classified into three types based on the type of fuzzy reasoning and fuzzy if-then rules used, i.e. Mamdani-typed FIS [3], [4]; Tsukamoto-typed FIS [5]; and Takagi-Sugeno-typed FIS [6].

### *2.2. Functional Approximation*

ANN or NN is the result of research using mathematical model formulations based on nervous system operations. As the name implies, NN shows computing techniques that attempt to simulate a network of nerve cells (neurons) from the biological nerve system. Unlike traditional mathematical models, which are machine-programmed, NN studies and recognizes the relationship between input and output, so that it can accommodate many inputs in parallel and encode information in distributed modes. The brain basically learns from the experience, so NN can learn based on the relationship between input and output chosen from previous experience. NN can also do parallel processing, which makes NN very fast. NN is able to identify and study the relationship between input and output of a multi-dimensional non-linear system. NN's performance potential depends on its architecture, which consists of several artificial neurons that act as simple computing elements that are connected at the ends by variable weights. There are various NN models found in the literature (**Figure 1**). Neuron settings or topologies in layer form connection patterns within and between layers, which are generally known as network architectures. The process of modifying / changing weights between multiple layers of the network with the aim of achieving the expected results (output) is known as network training, while internal settings or processes occur when the network is trained called learning.

Genetic Algorithm (GA) is a biologically inspired computing technique for optimization and heuristic searches. GA was developed by Holland [7] in the mid-1960s based on the simple theory of evolution, in which algorithms work with binary strings to produce the next generation using genetic operators. The three most common terminology used in GA is a gene, which acts as an entity that represents the characteristics of each individual; a chromosome consisting of strings or collections of genes that represent optimization solutions and a population is a collection of chromosomes.



**Figure 1.** Machine Intelligence Landscape.

Evolutionary Strategies (ES) was developed by Rechenberg and Schwefel [8] at about the same time as the development of GA by Holland. Both have similarities, because the rationale used by ES is almost the same as the rationale used by GA. ES is equipped with independent adaptability for strategic parameters. The main difference between ES and GA lies in the optimum candidate solution representation, whereas chromosome in ES consists of a vector containing real numbers, while the chromosome in GA consists of vectors containing binary strings. Evolutionary Programming (EP) was first developed by Fogel in the 1960s [9]. At this time EP is widely used with ES in terms of real number representation, the description of mutations that are normally distributed, and the variance of mutations. Genetic Programming (GP) was first introduced by Koza [10] by extending GA capabilities based on ideas and principles of biological evolution to deal with complex problems using a test model and the best choice among a series of choices represented by a string. GP is a computer program that works automatically based on the Darwinian selection principle in selecting the best solution. Swarm intelligence (SI) is one of the fields in SC that works on the basis of self-organized principles, in which the system consists of components that work collectively, decentralized and autonomous. This concept was introduced by Gerardo Beni and Jing Wang in 1989, in the context of cellular robotic systems [11]. The SI system is usually a population consisting of several individuals or components that interact with each other locally in a particular environment. This system was developed inspired by nature, especially biological systems. Some individuals in the population follow very simple rules, even though there is no centralized control structure that governs how individuals must behave. The rules are followed locally and to a certain degree are random, but the interaction between these individuals results in global behavior of a smart system, which is not known by each individual.

### 2.3. Hybrid System or Hybrid Intelligence

**Table 1** provides the performance comparison of several SC computing techniques that work independently without any collaboration with others in the context of hybrid systems. It can be concluded, that classical AI has many disadvantages compared to modern SC. PR can be concluded as SC technique with good results, having few weaknesses or almost no weakness. FS has weaknesses related to adaptation, learning and optimization. While NN is superior when it is used for problems that require learning. For optimization, the EC is superior to FS and NN.

Hybrid System (HS) or Hybrid Intelligence (HI) can be simply defined as collaboration or a combination of several computing techniques, for example between NN and FS, which produce Neuro-Fuzzy System (NFS), one of which is Adaptive Neuro Fuzzy Inference System (ANFIS). Merging FL and NN will combine the advantages of each and at the same time reduce the weaknesses of both.

**Table 1.** Soft Computing Comparison (modified from [12]).

No.	Parameters	Classical AI	PR	FS	NN	EC
1	Adaptability	Good	Good	Rather bad	Good	Slightly good
2	Expert knowledge representation	Good	Good	Good	Bad	Slightly good
3	Explanation ability	Good	Slightly good	Good	Bad	Slightly good
4	Fault tolerance	Bad	Good	Good	Good	Good
5	Imprecision tolerance	Bad	Good	Good	Good	Good
6	Learning capability	Bad	Good	Bad	Good	Good
7	Maintainability	Slightly good	Slightly good	Slightly good	Good	Slightly good
8	Mathematical model	Slightly good	Good	Slightly good	Bad	Bad
9	Non-linearity	Slightly good	Good	Good	Good	Good
10	Optimization ability	Bad	Slightly good	Bad	Slightly good	Good
11	Real time operation	Bad	Good	Good	Slightly good	Slightly good
12	Uncertainty tolerance	Bad	Good	Good	Good	Good

### 3. Application of Soft Computing Techniques in Mineral Resources Engineering

In mining activities, it is often faced with difficult and complex decision making which generally involves uncertainty, insufficiency, inaccuracy of data and information. These difficulties are best treated by using SC, through utilizing the superiority of SC for its high tolerance for imprecision, uncertainty, inaccuracy and partial truth. The review of SC application in mineral resources engineering focusing on the mining engineering will be carried out on the main mining activities such as prospecting, grade distribution modeling and resource estimation; mining method selection; mining equipment selection; rock classification; parameters estimation; rock performance; blasting; mining hydrogeology and optimization cases.

**Table 2.** Application of SC in Prospecting, Grade Distribution Modeling and Resource Estimation.

No.	Author(s)	Ref.	Year	Topic(s)	EXS	PR	FS	NN	EC	HS
1	Dimitrakopoulos	[13]	1990	Grade distribution	✓					
2	Dimitrakopoulos	[14]	1993	Grade distribution	✓					
3	Kapageridis	[15]	1999	Grade distribution				✓		
4	Chatterjee et al.	[16]	2008	Grade distribution				✓		
5	Mahmoudabadi et al.	[17]	2009	Grade distribution				✓	V (GA)	
6	Tahmasebi et al.	[18]	2010	Grade distribution						✓ (ANFIS)
7	Li et al.	[19]	2010	Grade distribution				✓		
8	Dutta et al.	[20]	2010	Resource estimation				✓	V (GA)	
9	Tahmasebi et al.	[21]	2012	Grade distribution					V (GA)	✓ (ANFIS)
10	Dhekne et al.	[22]	2014	Rock fragment char.						✓ (NFS)
11	Granek	[23]	2016	Prospecting				✓		
12	Setyadi	[24]	2016	Prospecting			✓			
13	Jahangiri et al.	[25]	2018	Rock mineral char.				✓		

GA: Genetic Algorithm; NFS: Neuro-Fuzzy System; ANFIS: Adaptive Neuro Fuzzy Inference System

From **Table 2**, it can be seen, that the application of SC in prospecting, grade distribution modeling and resource estimation has begun in the 1990s with expert system computing techniques (EXS) categorized as classical AI, which is essentially expert-driven. The application of modern SC in mining exploration began around the early 2000s, which was generally data-driven using NN, but then in the late 2000s was developed by incorporating optimization techniques using GA. Subsequent developments were characterized by the application of HS using ANFIS, which has advantages because of the possibility of adopting expert judgement into the FS in the form of fuzzy membership function (FMF). The HS using ANFIS can be seen as having advantages over comparable methods, namely geostatistics, in terms of tolerance to imprecision, uncertainty, inaccuracy, partial truth and lack of information that is treated by means tuning the FIS by the NN training process. Prospecting generally uses SC based on expert-driven, while grade distribution modeling and resource estimation have the characteristics of data-driven.

**Table 3.** Application of SC in Mining Method Selection (modified from [26]).

No.	Author(s)	Ref.	Year	EXS	PR	FS	NN	EC	HS
1	Yun and Huang	[27]	1987			✓			
2	Bandopadhyay & Venkatasubramanian	[28]	1988	✓					
3	Gershon et al.	[29]	1993	✓					
4	Yiming et al.	[30]	1995	✓					
5	Guray et al.	[31]	2003	✓					
6	Bitarafan and Ataei	[32]	2004			✓			
7	Ataei et al.	[33]	2008			✓			
8	Azadeh et al.	[34]	2010			✓			
9	Namin et al.	[35]	2011			✓			

**Table 4.** Application of SC in Mining Equipment Selection (modified from [26]).

No.	Author(s)	Ref.	Year	EXS	PR	FS	NN	EC	HS
1	Banddopadhyay	[36]	1987			√			
2	Bandopadhyay & Venkatasubramanian	[37]	1987	√					
3	Clarke et al.	[38]	1990	√					
4	Denby & Schofield	[39]	1990	√		√			
5	Amirkhanian & Baker	[40]	1992	√					
6	Haidar & Naoum	[41]	1996					√ (GA)	
7	Bascetin & Kesimal	[42]	1999			√			
8	Haidar et al.	[43]	1999					√ (GA)	
9	Ganguli & Bandopadhyay	[44]	2002	√		√			
10	Marzouk and Mosehlhi	[45]	2002					√ (GA)	
11	Marzouk and Mosehlhi	[46]	2004					√ (GA)	
12	Bascetin	[47]	2004			√			
13	Ipchar & Goktan	[48]	2006			√			
14	Li & Song	[49]	2009					√ (GA)	
15	Bazzazi et al.	[50]	2011	√		√			

GA: Genetic Algorithm

**Table 5.** Application of SC in Rock Classification (modified and updated from [26]).

No.	Author(s)	Ref.	Year	Class	EXS	PR	FS	NN	EC	HS
1	Zhang et al.	[51]	1988	GU	√					
2	Juang & Lee	[52]	1989	RMR	√		√			
3	Butler & Franklin	[53]	1990	RMR, Q	√					
4	Juang & Lee	[54]	1990	RMR			√			
5	Aydin	[55]	2004	RMR			√			
6	Hamidi et al.	[56]	2010	RME			√			
7	Jalalifar et al.	[57]	2014	RMR			√			
8	Rad et al.	[58]	2015	RMR						√ (ANFIS)
9	Hussain et al.	[59]	2016	RMR				√		

RMR: Rock Mass Rating; RME: Rock Mass Excavability; Q: Q-System; Gu's Rock Classification

ANFIS: Adaptive Neural Network Fuzzy Inference System

**Tables 3, 4 and 5** represent activities in mining (selection and classification), which are essentially expert-driven and qualitative, in which expert judgement or opinion is crucial. To adopt and represent expert opinion, it is best to use EXS, PR or FS computing techniques. Literatures or references in the three tables, almost all of them do use EXS or FS. There are only two references in the three tables that use data-driven SC, namely [30] and [59], so that both references can be ascertained using sufficient data, because without sufficient data, learning by NN cannot be done. Although based on expert-driven, some references have used GA optimization techniques starting in the mid 1990s.

**Table 6** presents parameter estimation activities, which are generally very dominant based on data measurements, so that the modeling is carried out using computing techniques that are data-driven, namely NN or HS based on NFS, such as ANFIS. There are only three references in the table purely using SC based on expert-driven, namely [60] [65] and [67]. The application of EC-based optimization techniques is mostly used for estimation parameters with back analysis.

**Table 7** presents activities on reliability analysis, which are generally expressed by inverse of failure probability, so that it is best presented using PR such as [79] and [85], which are new for the application of SC in the mining engineering, whereas other references use FS. Modeling using NN is usually based on data from several similar cases. Modeling with HS (NFS and ANFIS) is based on data and guided by expert opinion. The use of EC-based optimization techniques is used so that reliability and rock performance models converge on the results closest to the actual conditions.

**Table 6.** Application of SC in Parameter Estimation (modified and updated from [26]).

No.	Author(s)	Ref.	Year	Parameter(s)	EXS	PR	FS	NN	EC	HS
1	Kayabasi et al.	[60]	2003	Mod. Deformation (Ed)			✓			
2	Sonmez et al.	[61]	2006	Mod. Elast. (Ee)				✓		
3	Beiki et al.	[62]	2010	Mod. Deformation (Ed)				✓	✓ (GP)	
4	Vardakos et al.	[63]	2012	Mod. Elast. (Ee); Ver. Stress ( $\sigma_v$ ); Hor. Stress ( $\sigma_h$ ); Poi. Rat. ( $\nu$ ); Fric. Ang. ( $\phi$ )				✓	✓ (GA)	
5	Singh et al.	[64]	2001	Unc. Comp. Strength (UCS); Tensile Strength ( $\sigma_t$ )						
6	Sonmez et al.	[65]	2004	Unc. Comp. Strength (UCS); Mod. Deformation (Ed)			✓			✓ (NFS)
7	Gokceoglu et al.	[66]	2004	Unc. Comp. Strength (UCS)				✓		✓ (ANFIS)
8	Rezaei et al.	[67]	2014	Unc. Comp. Strength (UCS)						
9	Singh et al.	[68]	2017	Unc. Comp. Strength (UCS); Tensile Strength ( $\sigma_t$ ), Point Load Index						
10	Samuel and Jha	[69]	2003	Hydraulic Parameters (K, Ss)					✓ (GA)	
11	Bagheripour	[70]	2014	Rock Permeability (k)				✓	✓ (GA)	
12	Lee & Sterling	[71]	1992	Failure Mode				✓		
13	Rafiai et al.	[72]	2013	Failure Criteria				✓		
14	Bassera et al.	[73]	2015	Optimum parameters for spur dike protection						
15	Kaunda & Asbury	[74]	2016	Rock Brittleness; Rock Strength, Mechanical Excavation, Elastic Strength				✓	✓ (PSO)	✓ (ANFIS)
16	Feng et al.	[75]	2006	Viscoelastic Mode					✓ (GP), ✓ (PSO)	

GP: Genetic Programming; GA: Genetic Algorithm; NFS: Neuro-Fuzzy System; ANFIS: Adaptive Neuro-Fuzzy Inference System; PSO: Particle Swarm Optimization

**Table 7.** Application of SC in Rock Performance and Reliability Analysis (modified and updated from [26]).

No.	Author(s)	Ref.	Year	Parameter(s)	EXS	PR	FS	NN	EC	HS
1	Deng & Lee	[76]	2001	Displacement / deformation				✓	✓ (GA)	
2	Li et al.	[77]	2006	Displacement / deformation			✓	✓		
3	Li et al.	[78]	2007	Displacement / deformation			✓		✓ (GA), ✓ (GP)	
4	Li et al.	[79]	2013	Displacement / deformation		✓	✓			
5	Ghoobasti et al.	[80]	2014	Displacement / deformation				✓	✓ (PSO)	
6	Darabi et al.	[81]	2012	Convergence, subsidence				✓		
7	Ghasemi et al.	[82]	2014	Pillar dimension			✓			
8	Yurdakul et al.	[83]	2014	Cutting energy						✓ (NFS)
9	Yang & Zhang	[84]	1997	Realibility, stability analysis				✓		
10	Javadi et al.	[85]	2017	Realibility, roof fall analysis		✓	✓			✓

GA: Genetic Algorithm; GP: Genetic Programming; PSO: Particle Swarm Optimization; NFS: Neuro-Fuzzy System

**Table 8.** Application of SC in Blasting (modified and updated from [26]).

No.	Author(s)	Ref.	Year	Class	EXS	PR	FS	NN	EC	HS
1	Singh et al.	[86]	2004	PPV, BFQ				√		
2	Lu	[87]	2005	PPV, BFQ, PPA, FBF				√		
3	Monjezi et al.	[88]	2006	BFR, MPI, TEX				√		
4	Remennikov & Rose	[89]	2007	AFp, Afi				√		
5	Azimi et al.	[90]	2010	BD			√			
6	Fisne et al.	[91]	2011	PPV			√			
7	Monjezi et al.	[92]	2011	BBB, BFQ, BP				√	√ (GA)	
8	Bahrani et al.	[93]	2011	BRF				√		
9	Ataei & Kamali	[94]	2012	PPV						√ (NFS)
10	Esmaili et al.	[95]	2012	BBB				√		√ (ANFIS)
11	Sun et al.	[96]	2013	BOB				√		
12	Verma & Singh	[97]	2013	PWV						√ (NFS)
13	Hajihassani et al.	[98]	2014	BAO				√	√ (PSO)	
14	Ghasemi et al.	[99]	2014	BFR			√	√		
15	Dindarloo	[100]	2015	PPV				√	√ (GP), √ (GEP)	
16	Faradonbeh et al.	[101]	2016	BFR					√ (GP), √ (GEP)	

GA: Genetic Algorithm; GP: Genetic Programming; GEP: Genetic Equation Programming

PSO: Particle Swarm Optimization; NFS: Neuro-Fuzzy System; ANFIS: Adaptive Neuro Fuzzy Inference System

PPV: Peak Particle Velocity; PPA: Peak Particle Acceleration; BFQ: Blasting Induced Frequency

FBF: Frequency Bandwidth Factor; BFR: Blasting-induced Fly Rock; MPI: Muck Pile Ratio; TEX: Total Explosive Required

AFp: Air Pressure Pulse; Afi: Air Pressure Impulse; BD: Blasability Designation; BBB: Blasting-induced Backbreak

BP: Blasting Parameters; BRF: Blasting-induced Rock Fragmentation; BOB: Blasting-induced Overbreak

PWV: P-Wave Velocity; BAO: Blasting-induced Air Overpressure;

**Table 8** presents blasting-related mining activities that can be concluded generally based on data-driven guided by expert opinions and optimization techniques. The prediction of some blasting parameters is generally based on existing primary measured data. Rarely is the prediction done based on pure expert opinion. There are only 2 references in the table, namely [90], which models BD and [91], which models PPV. Except for both, almost all references in the table, model PPV based on existing measured data. The use of optimization techniques is intended to achieve most likely values closest to real values.

**Table 9** gives an overview of the SC application in mining hydrogeology. It can be concluded, that expert-driven SC, data-driven SC and evolutionary-based SC are used evenly in mining hydrogeology related cases. There are only two references in the table that use purely expert-driven SC, one of which is [103] for most suitable dewatering method selection. This is consistent with the previous explanation that related to choices, usually the subjective factors of the expert become important. Other references based on expert-driven are [110] and [111], but with a deeper review, it can be concluded that reference [111] is based on an expert-driven using FS in combination with data-driven using geostatistics (GS). **Table 10** presents the SC application in optimization, which generally uses evolutionary - based SC, which is indeed suitable for optimization.

#### 4. Conclusion

SC has the advantage over HC in terms of its tolerance for uncertainty, inaccuracy, imprecision, partial truth, human linguistic, flexibility and operational ease. With these advantages, then several problems in mining engineering that are dominated with uncertainty problems and approximate reasoning as well as subjective problems or combinations with objective data-driven problems will very well be terated using SC. However, with so many advantages over HC, SC has not yet been able to replace HC's position in modeling phenomena with detailed deterministic description involving unsteady state phenomena.



**Table 9.** Application of SC in Mining Hydrogeology.

No.	Author(s)	Ref.	Year	Topic(s)	EXS	PR	FS	NN	EC	HS
1	Coppola Jr. et al.	[102]	2003	Complex GW management				✓		
2	Golestanifar & Ahangari	[103]	2012	Open pit GW dewatering method selection			✓			
3	Sahay et al.	[104]	2013	Estimation of GWL in hard rock						✓ (ANFIS)
4	Jiang et al.	[105]	2013	Open pit GW dewatering					✓ (GA)	
5	El-Ghandour <sup>1</sup> & Elsaid	[106]	2013	GW management					✓ (GA), ✓ (PSO)	
6	Najafi et al.	[107]	2015	Out seam dillution LW coal mine			✓			
7	Chang et al.	[108]	2016	Estimation of GWL				✓	✓ (SOM)	
8	Alizamir et al.	[109]	2017	Modeling GW heavy metal concentration				✓		
9	Li et al.	[110]	2017	GW environment in mining			✓			
10	Theodoridou et al.	[111]	2017	Estimation of GWL using FS and GS			✓			✓ (ANFIS)
11	Gholami et al.	[112]	2017	GW quality assessment			✓			✓ (ANFIS)
12	Fattahi et al.	[113]	2018	Dissolved metal level in ARD					✓ (GA)	✓ (ANFIS)
13	Jalalkamali and Jalalkamali	[114]	2018	Prediction of GW quality indeces						✓ (ANFIS)

GA: Genetic Algorithm; PSO: Particle Swarm Optimization; SOM: Self Organized Management  
 ANFIS: Adaptive Neuro Fuzzy Inference System; FS: Fuzzy System; GS: Geostatistics  
 GWL: Groundwater Level; ARD: Acid Rock Drainage

**Table 10.** Application of SC in Optimization Related Cases.

No.	Author(s)	Ref.	Year	Topic(s)	EXS	PR	FS	NN	EC	HS
1	Wu et al.	115	2005	Cost-effective sampling					✓ (GA)	
2	Moharram et al.	116	2012	Optimal GW management					✓ (GA)	
3	Jiang et al.	105	2013	GW dewatering optimization					✓ (GA)	
4	Safavi et al.	117	2013	Optimal aquifer management						✓ (ANFIS)
5	Izquierdo et al.	118	2014	DSS for mining solution spaces		✓			✓ (PSO), ✓ (SOM)	
6	Mohammadi et al.	119	2015	CoG Optimization					✓ (ICA)	
7	Jang et al.	120	2015	DSS for dillution ore loss						✓ (ANFIS)
8	Cetin & Dowd	121	2016	CoG Optimization					✓ (GA)	
9	Ahmadi et al.	122	2018	CoG Optimization					✓ (GA)	

GA: Genetic Algorithm; PSO: Particle Swarm Optimization; SOM: Self-Organized Management  
 ICA: Imperilist Competitive Algorithm; ANFIS: Adaptive Neuro Fuzzy Inference System  
 GW: Groundwater; DSS: Decision Support System; CoG: Cut off Grade

## References

- [1] McCulloch W S and Pitts W 1943 *A Logical Calculus of The Ideas Immanent in Nervousactivity*; Bull. Math. Biophys; Vol. **5**; pp. 115–133
- [2] Zadeh L A 1965 *Fuzzy Sets*; Information and Control; Vol. **8**; pp 338–358; (doi:10.1016/S0019-9958 (65)90241-X)
- [3] Mamdani E H 1977 *Application of Fuzzy Logic to Approximate Reasoning using Linguistic Synthesis*; IEEE Trans. on Computers; Vol. **26**, No. 12; pp. 1182–1191
- [4] Mamdani E H and Assilian S 1975 *An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller*; Intl. Journal of Man-Machine Studies; Vol. **7**; No. 1; pp 1-13
- [5] Tsukamoto Y 1979 *An Approach to Fuzzy Reasoning Method*; North-Holland; pp. 137–149
- [6] Sugeno M 1988 *Fuzzy Control*; North-Holland
- [7] Holland J H 1975 *Adaptation in Natural and Artificial Systems*; Ann Arbor; University of Michigan Press
- [8] Schwefel H P 1995 *Evolution and Optimum Seeking*; John Wiley and Sons
- [9] Fogel L J 1962 *Autonomous Automata*; Industrial Research, Vol. **4**; pp. 14-19
- [10] Koza J 1992 *Genetic Programming*; MIT Press; Cambridge; MA
- [11] Beni G, Wang J 1989 *Swarm Intelligence in Cellular Robotic Systems*; Proceed. NATO Advanced Workshop on Robots and Biological Systems; Tuscany; Italy; (doi:10.1007/978-3-642-58069-7\_38)
- [12] Omolaye P O, Mom J M, Igwe G A 2017 *A Holistic Review of Soft Computing Techniques*; Applied and Computational Mathematics; Vol.**6**; No. 2; pp. 93-110; (doi: 10.11648/j.acm.20170602.15)
- [13] Dimitrakopoulos R 1990 *Towards Intelligent Systems for Geostatistical Ore Reserve Estimation*; Intl. J. of Surface Mining and Reclamation; Vol. **4**; pp. 37-41
- [14] Dimitrakopoulos R 1993 *Artificially Intelligent Geostatistics: a Framework Accomodating Qualitative Knowledge-Information*; Mathematical Geology; Vol. **25**; No. 3; pp. 261-280
- [15] Kapageridis I K 1999 *Application of Artificial Neural Network Systems to Grade Estimation from Exploration Data*; Dissertation; School of Chemical, Environmental, and Mining Eng.; University of Nottingham.
- [16] Chatterjee S, Bhattacharjee A, Amanta B, Pal S K 2006 *Ore Grade Estimation of a Limestone Deposit in India using an Artificial Neural Network*; Applied GIS; Vol. **2**; No. 1; Monash University Press.
- [17] Mahmoudabadi H, Izadi M, Menhaj M B 2009 *A Hybrid Method for Grade Estimation using Genetic Algorithm and Neural Networks*; Computer Geoscience; Vol.**13**; pp. 91–101; (doi 10.1007/s10596-008-9107-9)
- [18] Tahmasebi P and Hezarkhani A 2010 *Application of Adaptive Neuro-Fuzzy Inference System for Grade Estimation - Case Study Sarcheshmeh Porphyry Copper Deposit – Kerman – Iran*; Australian Journal of Basic and Applied Sciences; Vol. **4**; No. 3; pp. 408-420
- [19] Xiao-li Li X L, Xie Y L, Guo Q J, Li L H 2010 *Adaptive Ore Grade Estimation Method for The Mineral Deposit Evaluation*; Mathematical and Computer Modelling; Vol. **52**; pp. 1947-1956; (doi:10.1016/j.mcm.2010.04.018)
- [20] Dutta S, Bandopadhyay S, Ganguli R, Misra D 2010 *Machine Learning Algorithms and Their Application to Ore Reserve Estimation of Sparse and Imprecise Data*; J. Intelligent Learning Systems & Applications; Vol. **2**; pp. 86-96; (doi:10.4236/jilsa.2010.22012)
- [21] Tahmasebi P and Hezarkhani A 2012 *A Hybrid Neural Networks-Fuzzy Logic-Genetic*

- Algorithm for Grade Estimation*; Computers & Geosciences; Vol. **42**; pp. 18–27; (doi:10.1016/j.cageo.2012.02.004)
- [22] P Y Dhekne, Manoj Pradhan and R K Jade 2014 *Artificial Intelligence and Prediction of Rock Fragmentation*; in: *Mine Planning and Equipment Selection*; Drebenstedt, C. and Singhal, R. (eds.); Springer International Publishing; Switzerland; (doi: 10.1007/978-3-319-02678-7\_86,)
- [23] Granek J 2016 *Application of Machine Learning Algorithms to Mineral Prospectivity Mapping*; Dissertation; The Faculty of Graduate and Postdoctoral Studies; The University of British Columbia
- [24] Setyadi H 2016 *Mineral Deposit Prosperity Modeling Based on the Geological Domain, Case Study at Seruyung High Sulphidation Epithermal (HSE) Au*; Dissertation; Faculty of Mining and Petroleum Engineering, Bandung Inst. of Tech.
- [25] Jahangiri M, Riabi S R G, Tokhmechi B 2018 *Estimation of Geochemical Elements using a Hybrid Neural Network-Gustafson-Kessel Algorithm*; Journal of Mining & Environment; Vol. **9**; No.2; pp. 499–511; (doi: 0.22044/jme.2017.5513.1363).
- [26] Jang H and Topal E 2014 *A Review of Soft Computing Technology Applications in Several Mining Problems*; Applied Soft Computing; Vol. **22**; pp. 638–651
- [27] Yun Q and Huang G 1987 *A Fuzzy Set Approach to The Selection of Mining Method*; Min. Sci. Technol.; Vol. **6**; pp. 9–16
- [28] Bandopadhyay S and Venkatasubramanian P 1988 *A Rule-Based Expert System Formining Method Selection*; CIM Bull.; Vol. **81**; pp. 84–88
- [29] Gershon M, Bandopadhyay S, Panchanadam V 1993 *Mining Method Selection: a Decision Support System Integrating Multi-Attribute Utility Theory and Expert Systems*; in: Proceedings of the 24<sup>th</sup> International Symposium on the Application of Computers in Mine Planning; pp. 11–18
- [30] Yiming W, Guangxu T, Xiaohua C 1995 *A Study on The Neural Network Based Expert System for Mining Method Selection*; J. Comput. Appl. Softw.; Vol. **5**; No. 09
- [31] Guray C, Celebi N E, Atalay V, Pasamehmetoglu A G 2003 *Ore-Age: a Hybrid System for Assisting and Teaching Mining Method Selection*; Expert Syst. Appl. Vol. **24**; pp. 261–271
- [32] Bitarafan M and Ataei M 2004 *Mining Method Selection by Multiple Criteria Decision Making Tools*; J. South Afr. Inst. Min. Metal.; Vol. **104**; pp. 493–498
- [33] Ataei M, Jamshidi M, Sereshki F, Jalali, S 2008 *Mining Method Selection by AHP Approach*; J. South. Afr. Inst. Min. Metal.; Vol. **108**; pp. 741–749
- [34] Azadeh A, Osanloo M, Ataei M 2010 *A New Approach to Mining Method Selection based on Modifying the Nicholas Technique*; Appl. Soft Comput.; Vol. **10**; pp. 1040–1061
- [35] Namin F, Shahriar K, Bascetin A, Ghodsypour S 2011 *FMMSIC: a Hybrid Fuzzy-based Decision Support System for MMS - in Order to Estimate Interrelationships between Criteria*; J. Operat. Res. Soc.; Vol. **63**; pp. 218–231
- [36] Bandopadhyay S 1987 *Partial Ranking of Primary Stripping Equipment in Surface Mine Planning*; Int. J. Surf. Min. Reclam. Environ.; Vol. **1**; pp. 55–59
- [37] Bandopadhyay S and Venkatasubramanian P 1987 *Expert Systems as Decision Aid in Surface Mine equipment Selection*; Int. J. Surf. Min. Reclam. Environ.; Vol. **1**, pp. 159–165
- [38] Clarke M, Denby B, Schofield D 1990 *Decision Making Tools for Surface Mine Equipment Selection*; Min. Sci. Technol.; Vol. **10**; pp. 323–335
- [39] Denby B, Schofield D 1990 *Applications of Expert Systems in Equipment Selection for Surface Mine Design*; Int. J. Surf. Min. Reclam. Environ.; Vol. **4** pp. 165–171

- [40] Amirkhanian S N, Baker N J 1992 *Expert System for Equipment Selection for Earth-Moving Operations*; J. Construct. Eng. Manage.; Vol. **118**; pp. 318–331
- [41] Haidar A and Naoum S 1996 *Open Cast Mine Equipment Selection using Genetic Algorithms*; Int. J. Surf. Min. Reclam.; Vol. **10**; pp. 61–67
- [42] Bascetin A, Kesimal A 1999 *The Study of a Fuzzy Set Theory for The Selection of an Optimum Coal Transportation System from Pit to The Power Plant*; Int. J. Surf.Min. Reclam. Environ.; Vol. **13**; pp. 97–101
- [43] Haidar A, Naoum S, Howes R, Tah J 1999 *Genetic Algorithms Application and Testing for Equipment Selection*; J. Const. Eng. Manage.; Vol. **125**; pp. 32–38
- [44] Ganguli R, Bandyopadhyay S 2002 *Expert System for Equipment Selection*; Int. J.Surf. Min. Reclam. Environ.; Vol. **16**; pp. 163–170
- [45] Marzouk M and Moselhi O 2002 *Selecting Earth Moving Equipment Fleets using Genetic Algorithms*; in: Proceedings of the Winter Simulation Conference; IEEE; pp. 1789–1796.
- [46] Marzouk M and Moselhi O 2004 *Multi Objective Optimization of Earth Moving Operations*; J Construct. Eng. Manage.; Vol. **130** pp. 105–113
- [47] Bascetin A 2004 *Technical Note: an Application of The Analytic Hierarchy Process in Equipment Selection at Orhaneli Open Pit Coal Mine*; Min. Technol; Vol. **113**; pp. 192–199
- [48] Iphar M and Goktan R 2006 *An Application of Fuzzy Sets to The Diggability Index Rating Method for Surface Mine Equipment Selection*; Int. J. Rock Mech. Min. Sci.; Vol. **43**; pp. 253–266
- [49] Li X and Song X 2009 *Application of Genetic Algorithm to Optimize The Equipment of Coal Mine*; in: IEEE International Conference on Computational Intelligenceand Software Engineering (CiSE 2009); pp. 1–3
- [50] Bazzazi A A, Osanloo M, Karimi B 2011 *Deriving Preference Oder of Open Pit Mines Equipment Through MADM Methods: Application of Modified VIKORmethod*; Expert Syst. Appl.; Vol. **38**; pp. 2550–2556
- [51] Zhang Q, Mo YB, Tian S F 1988 *An Expert System for Classification of Rock Masses*, in: The 29<sup>th</sup> US Symposium on Rock Mechanics 1988
- [52] [117] Juang C and Lee D 1989 *Development of an Expert System for Rock Mass Classification*; Civil Eng. Syst.; Vol. **6**; pp. 147–156
- [53] Juang C and Lee D 1990 *Rock Mass Classification using Fuzzy Sets*, in: Proceedings ofthe 10<sup>th</sup> Southeast Asian Geotechnical Conference; Chinese Institute of Civil and Hydraulic Engineering; Taipei, Taiwan; pp. 309–314
- [54] Butler A and Franklin J 1990 *Classex: an Expert System for Rock Mass Classification*; in: ISRM Internationl Symposium 1990
- [55] Aydin A 2004 *Fuzzy Set Approaches to Classification of Rock Masses*; Eng. Geol.; Vol. **74**; pp. 227–245
- [56] Hamidi J K, Shahriar K, Rezai B, Bejari H 2010 *Application of Fuzzy Set Theoryto Rock Engineering Classification Systems: an Illustration of The Rock Mass Excavability Index*; Rock Mech. Rock Eng.; Vol. **43**; pp. 335–350
- [57] Jalalifar H, Mojedifar S, Sahebi A A 2014 *Prediction of Rock Mass Rating using Fuzzy Logic and Multi-Variable RMR Regression Model*; Int. J. Min. Sci. Technol.; Vol. **24**; pp. 237–244
- [58] Rad H N, Jalali Z, Jalalifar H 2015 *Prediction of Rock Mass R ating System based on Continuous Functions using Chaos–ANFIS Model*; Intl. Journal of Rock Mechanics & Mining Sciences; Vol. **73**; pp. 1–9
- [59] Hussain S, Mohammad N, Khan M, Rehman Z U, Tahir M 2016 *Comparative Analysis of Rock Mass Rating Prediction Using Different Inductive Modeling Techniques*; Intl. Journal of Mining Engineering and Mineral Processing; Vol. **5**;

- No. 1; pp. 9-15; (doi: 10.5923/j.mining.20160501.02)
- [60] Kayabasi A, Gokceoglu C, Ercanoglu M 2003 *Estimating the Deformation Modulus of Rock Masses: a Comparative Study*; Intl. J. Rock Mech. Min. Sci.; Vol. **40** pp. 55–63
  - [61] Sonmez H, Gokceoglu C, Nefeslioglu H, Kayabasi A 2006 *Estimation of Rock Modulus: for Intact Rocks with an Artificial Neural Network and for Rock Masses with a New Empirical Equation*; Int. J. Rock Mech. Min. Sci.; Vol. **43**; pp. 224–235
  - [62] Beiki M, Bashari A, Majdi A 2010 *Genetic Programming Approach for Estimating The Deformation Modulus of Rock Mass using Sensitivity Analysis by Neural Network*; Int. J. Rock Mech. Min. Sci.; Vol. **47**, pp; pp. 1091–1103
  - [63] Vardakos S, Gutierrez M, Xia C 2012 *Parameter Identification in Numerical Modeling of Tunneling using the Differential Evolution Genetic Algorithm (DEGA)*; Tunnel. Undergr. Space Technol.; Vol. **28**; pp. 109–123
  - [64] Singh V, Singh D, Singh T 2001 *Prediction of Strength Properties of Some Schistose Rocks from Petrographic Properties using Artificial Neural Networks*; Int.J. Rock Mech. Min. Sci.; Vol. **38**; pp. 269–284
  - [65] Sonmez H, Tuncay E, Gokceoglu C 2004 *Models to Predict The Uniaxial Compressive Strength and The Modulus of Elasticity for Ankara Agglomerate*; Int. J. Rock Mech. Min. Sci.; Vol. **41**; pp. 717–729
  - [66] Gokceoglu C, Yesilnacar E, Sonmez H, Kayabasi A 2004 *A Neuro-Fuzzy Model for Modulus of Deformation of Jointed Rock Masses*; Comput. Geotech.; Vol. **31**; pp. 375–383
  - [67] Rezaei M, Majdi A, Monjezi M 2014 *An Intelligent Approach to Predict Unconfined Compressive Strength of Rock Surrounding Access Tunnels in Longwall Coal Mining*; Neural Comput. Appl.; Vol. **24**; pp. 233–241
  - [68] Singh R, Umrao, R K Ahmad M, Ansari M K, Sharma L K, Singh T N 2017 *Prediction of Geomechanical Parameters using Soft Computing and Multiple Regression Approach*; Measurement; Vol. **99**; pp. 108–119
  - [69] Samuel M P and Jha M K 2003 *Estimation of Aquifer Parameters from Pumping Test Data by Genetic Algorithm Optimization Technique*; J. Irrig. Drain Eng.; Vol. **129**; No. 5; pp. 348–359
  - [70] Bagheripour P 2014 *Committee Neural Network Model for Rock Permeability Prediction*; J. Appl. Geophys.; Vol. **104**; pp. 142–148
  - [71] Lee C and Sterling R 1992 *Identifying Probable Failure Modes for Underground Openings using a Neural Network*; Int. J. Rock Mech. Min. Sci. Geomech. Abstracts; pp. 49–67
  - [72] H Rafiai, A Jafari, A Mahmoudi 2013 *Application of ANN-based Failure Criteria to Rocks under Polyaxial Stress Conditions*; Int. J. Rock Mech. Min. Sci.; Vol. **59**; pp. 42–49
  - [73] Bassera H, Karamib H, Shamshirband S, Akiba S, Amirmojahedia M, Ahmad R, Jahangirzadeha A, Javidnia H 2015 *Hybrid ANFIS–PSO Approach for Predicting Optimum Parameters of a Protective Spur Dike*; Applied Soft Computing; Vol. **30**; pp. 642–649
  - [74] Kaunda R B and Asbury B 2016 *Prediction of Rock Brittleness using non Destructive Methods for Hard Rock Tunneling*; Journal of Rock Mechanics and Geotechnical Engineering; Vol. **30**; pp. 1–8
  - [75] Feng X T, Chen B R, Yang C, Zhou H, Ding X 2006 *Identification of Visco-Elastic Models for Rocks using Genetic Programming Coupled with The Modified Particle Swarm Optimization Algorithm*; Int. J. Rock Mech. Min. Sci.; Vol. **43**; pp. 789–801

- [76] Deng J and Lee C 2001 *Displacement Back Analysis for a Steep Slope at The Three Gorges Project Site*; Int. J. Rock Mech. Min. Sci.; Vol. **38**, pp. 259–268
- [77] Li W, Mei S, Zai S, Zhao S, Liang X 2006 *Fuzzy Models for Analysis of Rock Mass Displacements due to Underground Mining in Mountainous Areas*; Int. J. RockMech. Min. Sci.; Vol. **43**; pp. 503–511
- [78] Li W, Dai L F, Hou X B, Lei W 2007 *Fuzzy Genetic Programming Method for Analysis of Ground Movements due to Underground Mining*; Int. J. Rock Mech.Min. Sci.; Vol. **44**; pp. 954–961
- [79] Li W, Liu S J, Li J F, Ji Z H, Wang Q, Yin X 2013 *Ground Movement Analysis in Deep Iron Mine using Fuzzy Probability Theory*; Appl. Math. Model.; Vol. **37**; pp. 345–356
- [80] Choobbasti A J, Tavakoli H, Kutanaei S S 2014 *Modeling and Optimization of a Trench Layer Location around a Pipe Line using Artificial Neural Networks and Particle Swarm Optimization Algorithm*; Tunnel. Undergr. Space Technol.; Vol. **40**; pp. 192–202
- [81] Darabi A, Ahangari K, Noorzad A, Arab A 2012 *Subsidence Estimation utilizing Various Approaches – a Case Study Tehran No. 3 subway line*; Tunnel. Undergr.Space Technol.; Vol. **31**; pp. 117–127
- [82] Ghasemi E, Ataei M, Shahriar K 2014 *An Intelligent Approach to Predict Pillar Sizing in Designing Room and Pillar Coal Mines*; Int. J. Rock Mech. Min. Sci.; Vol. **65**; pp. 86–95
- [83] Yurdakul M, Gopalakrishnan K, Akdas H 2014 *Prediction of Specific Cutting Energy in Natural Stone Cutting Processes using The Neuro-Fuzzy Methodology*; Int. J.Rock Mech. Min. Sci.; Vol. **67**; pp. 127–135
- [84] Yang Y and Zhang Q 1997 *A Hierarchical Analysis for Rock Engineering using Artificial Neural Networks*; Rock Mech. Rock Eng.; Vol. **30**; pp. 207–222
- [85] Javadi M, Saeedi G, Shahriar K 2017 *Fuzzy Bayesian Network Model for Roof Fall Risk Analysis in Underground Coal Mines*; J.Applied Sci; Vol. **17**; No. 3; pp. 103-115
- [86] Singh T, Kanchan R, Verma A 2004 *Prediction of Blast Induced Ground Vibration and Frequency using an Artificial Intelligent Technique*; Noise Vib. Worldw.; Vol. **35**; pp. 7–15
- [87] Lu Y 2005 *Underground Blast Induced Ground Shock and Its Modelling using Artificial Neural Network*; Comput. Geotech.; Vol. **32**; pp. 164–178
- [88] Monjezi M, Singh T, Khandelwal M, S Sinha S, Singh V, Hosseini I 2006 *Prediction and Analysis of Blast Parameters using Artificial Neural Network*; Noise Vib.Worldw.; Vol.37; pp. 8–16.
- [89] Remennikov A M and Rose T A 2007 *Predicting the Effectiveness of Blast Wall Barriers using Neural Networks*; Int. J. Impact Eng.; Vol. **34**; pp. 1907–1923
- [90] Azimi Y, Osanloo M, Aakbarpour-Shirazi M, Bazzazi A A 2010 *Prediction of the Blastability Designation of Rock Masses using Fuzzy Sets*; Int. J. RockMech. Min. Sci.; Vol. **47**; pp. 1126–1140
- [91] Fis A, Kuzu C, Hüdaverdi T 2011 *Prediction of Environmental Impacts of Quarry Blasting Operation using Fuzzy Logic*; Environ. Monitor. Assess.; Vol. **174**; pp. 461–470
- [92] Monjezi M, Amini K, Yazdian V 2011 *Optimization of Open Pit Blast Parameters using Genetic Algorithm*; Int. J. Rock Mech. Min. Sci.; Vol. **48**; pp. 864–869
- [93] Bahrami A, Monjezi M, Goshtasbi K, Ghazvinian A 2011 *Prediction of Rock Fragmentation due to Blasting using Artificial Neural Network*; Eng. Comput.; Vol. **27**; pp. 177–181
- [94] Ataei M and Kamali M 2012 *Prediction of Blast-Induced Vibration by Adaptive*

- Neuro-Fuzzy Inference System in Karoun 3 Power Plant and Dam*; J. Vib. Control; Vol. **19**; pp. 1906–1914
- [95] Esmaeili M, Osanloo M, Rashidinejad F, Bazzazi A A, Taji M 2012 *Multiple Regression, ANN and ANFIS Models for Prediction of Backbreak in The Open Pit Blasting*; Eng. Comput.; pp. 1–10
- [96] Sun S, Liu J, Jihong W 2013 *Predictions of Overbreak Blocks in Tunnels based on The Wavelet Neural Network Method and The Geological Statistics Theory*; Math.Prob. Eng.; pp. 1–9
- [97] Verma A and Singh T 2013 *A Neuro-Fuzzy Approach for Prediction of Longitudinal Wave Velocity*; Neural Comput. Appl.; pp. 1–9
- [98] Hajihassani M, Armaghani D J, Sohaei H, Mohamad E T Marto A 2014 *Prediction of Air Blast Over Pressure Induced by Blasting using a Hybrid Artificial Neural Network and Particle Swarm Optimization*; Appl. Acoust.; Vol. **80**; pp. 57–67
- [99] Ghasemi E, Amini H, Ataei M, Khalokakaei R 2014 *Application of Artificial Intelligence Techniques for Predicting the Flyrock Distance Caused by Blasting Operation*; Arab. J. Geosci. 7 (2014) pp 193–202
- [100] Dindarloo S R 2015 *Prediction of Blast Induced Ground Vibrations via Genetic Programming*; Intl. Journal of Mining Science and Technology; Vol. **25**; pp. 1011–1015
- [101] Faradonbeh R S, Armaghani D J, Monjezi M, Mohamad E T 2016 *Genetic Programming and Gene Expression Programming for Fly Rock Assessment due to Mine Blasting*; Intl. Journal of Rock Mechanics & Mining Sciences; Vol. **88**; pp. 254–264
- [102] Coppola Jr E, Poulton M, Charles E, Dustman J, Szidarovszky F 2003 *Application of Artificial Neural Networks to Complex Groundwater Management Problems*; Natural Resources Research; Vol. **12**; No. 4
- [103] Golestanifar M and Ahangari K 2012 *Choosing an Optimal Groundwater Lowering Technique for Open Pit Mines*; Mine Water Environ.; Vol. **31**; pp. 192–198; (doi 10.1007/s10230-012-0196-2)
- [104] Sahay S, Banoudha A, Sharma R 2013 *Comparative Study of Soft Computing Techniques for Ground Water Level Forecasting in a Hard Rock Area*; International Journal of Research and Development in Applied Science and Engineering; Volume **4**; Issue 1
- [105] Jiang S, Kong X, Ye H, Zhou N 2013 *Groundwater Dewatering Optimization in The Shengli No. 1 Open Pit Coal Mine, Inner Mongolia, China*; Environ Earth Sci.; Vol. **69**; pp.187–196; (doi 10.1007/s12665-012-1946-y)
- [106] El-Ghandourl H A and Elsaid A 2013 *Groundwater Management using a New Coupled Model of Flow Analytical Solution and Particle Swarm Optimization*; International Journal of Water Resources and Environmental Engineering; Vol. **5**; No. 1; pp. 1-11; (doi: 10.5897/IJWREE12.028)
- [107] Najafi A B, Farsangi, M A E, Saeedi G R 2015 *A Fuzzy Logic Model to Predict The Out of Seam Dilution in Longwall Mining*; International Journal of Mining Science and Technology; Vol. **25**; pp. 91–98
- [108] Chang F J, Chang L C, Huang C W, Kao I F 2016 *Prediction of Monthly Regional Groundwater Levels Through Hybrid Soft Computing Techniques*; Journal of Hydrology; Vol. **541**; pp. 965–976
- [109] Alizamir M, Sobhanardakani S, Taghavi L 2017 *Modeling of GW Resources Heavy Metals Concentration using Soft Computing Methods: Application of Different Types of ANNs*; JCHR; Vol. **7**; No. 3; pp. 207-216
- [110] Li Z, Zhou B, Teng D, Yang W, Qiu D 2017 *Comprehensive Evaluation Method of Groundwater Environment in a Mining Area based on Fuzzy Set Theory*;

- Geosystem Engineering; Taylor and Francis; 21:2; pp. 103-112; (doi: 10.1080/12269328.2017.1386594)
- [111] Theodoridou P G, Varouchakis E A, Karatzas G P 2017 *Spatial Analysis of Groundwater Levels using Fuzzy Logic and Geostatistical Tools*; Journal of Hydrology; Vol. **555**; pp. 242–252
  - [112] Gholami V, Khaleghi M R, Sebghati M 2017 *A Method of Groundwater Quality Assessment based on Fuzzy Network CANFIS and Geographic Information System (GIS)*; Appl Water Sci; Vol. **7**; pp. 3633–3647; (doi 10.1007/s13201-016-0508-y)
  - [113] Fattahi H, Agah A, Soleimanpournmoghadam N 2018 *Multi-Output Adaptive Neuro-Fuzzy Inference System for Prediction of Dissolved Metal Levels in Acid Rock Drainage: a Case Study*; Journal of AI and Data Mining; Vol. **6**, No. 1, pp. 121-132
  - [114] Jalalkamali A and Jalalkamali N 2018 *Adaptive Network based Fuzzy Inference System - Genetic Algorithm Models for Prediction Groundwater Quality Indices: a GIS-based Analysis*; Journal of AI and Data Mining; Vol. **6**; No. 2, pp. 439-445; (doi: 10.22044/JADM.2017.1086)
  - [115] Wu J, Zheng C, Chien C C 2005 *Cost-Effective Sampling Network Design for Contaminant Plume Monitoring under General Hydrogeological Conditions*; Journal of Contaminant Hydrology; Vol. **77**; pp. 41–65
  - [116] Moharram S H, Gad M I, Saafan T A, Allah S K 2012 *Optimal Groundwater Management Using Genetic Algorithm in El-Farafra Oasis, Western Desert, Egypt*; Water Resour Manage.; Vol. **26**; pp. 927–948; (doi 10.1007/s11269-011-9865-3)
  - [117] Safavi H R, Chakraei I, Samani A K, Golmohammadi M H 2013 *Optimal Reservoir Operation Based on Conjunctive Use of Surface Water and Groundwater Using Neuro-Fuzzy Systems*; Water Resour Manage.; Vol. **27**; pp. 4259–4275; (doi 10.1007/s11269-013-0405-1)
  - [118] Izquierdo J, Montalvob I, García R P, Campbella E 2014 *Mining Solution Spaces for Decision Making in Water Distribution Systems*; Procedia Engineering; Vol. **70**; pp. 864 – 871
  - [119] Mohammadi S, Ataei M, Kakaie R, E Pourzamani E 2015 *Comparison of Golden Section Search Method and Imperialist Competitive Algorithm for Optimization Cut-off Grade - Case Study: Mine No. 1 of Golgohar*; Journal of Mining & Environment; Vol. **6**; No.1; pp. 63-71
  - [120] Jang H, Topala E, Kawamuraba Y 2015 *Decision Support System of Unplanned Dilution and Ore Loss in Underground Stopping Operations using a Neuro-Fuzzy System*; Applied Soft Computing; Vol. **32**; pp. 1–12
  - [121] Cetin E and Dowd P A 2016 *Multiple Cut-off Grade Optimization by Genetic Algorithms and Comparison with Grid Search Method and Dynamic Programming*; Journal of the Southern African Institute of Mining and Metallurgy; Vol. **116**; No.7; pp. 681-688
  - [122] Ahmadi M R and Shahabib R S 2018 *Cut off Grade Optimization in Open Pit Mines using Genetic Algorithm*; Resources Policy; Vol. **55**; pp. 184–191