A review of soft computing application in mineral resources engineering

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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 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 extra ordinary 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.

| 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 Impression 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   |

Table 1. Soft Computing Comparison (modified from [12]).
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 | ✓  | ✓ (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 | ✓  | ✓ (GA) |    |    |    |    |
| 9   | Tahmasebi et al. | [21] | 2012 | Grade distribution | ✓ | ✓ (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   | Batarafan 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   | Bandopadhyay [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 |    |    | √  |    |    | (GA) |
| 8   | Haidar et al. [43] | 2002 | √  |    |    | √  | (GA) |    |
| 9   | Ganguli & Bandopadhyay [44] | 2002 |    | √  |    | √  |    |    |
| 10  | Marzouk and Moselhi [45] | 2004 |    |    |    | √  | (GA) |    |
| 11  | Marzouk and Moselhi [46] | 2004 |    |    |    | √  | (GA) |    |
| 12  | Bascetin [47] | 2004 |    |    |    | √  |    |    |
| 13  | Iphar & 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) | √   | V  |    |    |    |    |
| 4   | Vardakos et al. [63] | 2012 | Mod. Elast. (Ee); Ver.Stress (σv); Hor. Stress (σh); Poi. Rat. (ν); Fric. Ang. (θ) | √   |    |    |    |    |    |
| 5   | Singh et al. [64] | 2001 | Unc. Comp. Strength (UCS); Tensile Strength (σt) | √   |    |    |    |    |    |
| 6   | Sonmez et al. [65] | 2004 | Unc. Comp. Strength (UCS); Mod. Deformation (Ed) | √   |    |    |    |    |    |
| 7   | Gokceoglu et al [66] | 2004 | Unc. Comp. Strength (UCS) |    |    |    |    | V(NFS) |    |
| 8   | Rezaei et al. [67] | 2014 | Unc. Comp. Strength (UCS) | √   |    |    |    |    |    |
| 9   | Samuel and Jha [68] | 2015 | Optimum parameters for spur dike protection | √   |    |    |    |    |    |
| 10  | Ghasemi et al. [69] | 2013 | Displacement / deformation | √   |    |    |    |    |    |
| 11  | Lee & Sterling [70] | 1992 | Failure Mode |    |    |    |    |    |    |
| 12  | Raifai et al. [71] | 2013 | Failure Criteria |    |    |    |    |    |    |
| 13  | Darabi et al. [72] | 2012 | Convergence, subsidence |    |    |    |    |    |    |
| 14  | Yurdakul et al. [73] | 2014 | Rock Bittleness, Rock Strength, Mechanical Excavation, Elastic Strength | √   |    |    |    |    |    |
| 15  | Feng et al. [74] | 2006 | Viscoelastic Mode |    |    |    |    |    |    |

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 | √   |    |    |    |    |    |
| 2   | Li et al. [77] | 2006 | Displacement / deformation | √   |    |    |    |    |    |
| 3   | Li et al. [78] | 2007 | Displacement / deformation | √   |    |    |    | V(GA), V(GP) |    |
| 4   | Li et al. [79] | 2013 | Displacement / deformation | √   |    |    |    |    |    |
| 5   | Ghobbasti et al. [80] | 2014 | Displacement / deformation | √   |    |    |    |    |    |
| 6   | Darabi et al. [81] | 2012 | Convergence, subsidence |    |    |    |    |    |    |
| 7   | Ghasemi et al. [82] | 2014 | Pillar dimension |    |    |    |    |    |    |
| 8   | Yurdakul et al. [83] | 2014 | Cutting energy |    |    |    |    |    |    |
| 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 | √   |    |    |    |    |    |
| 8   | Bahrami et al. | [93] | 2011 | BRF | √   |    |    |    |    |    |
| 9   | Ataei & Kamali | [94] | 2012 | PPV | √ (NFS) |    |    |    |    |    |
| 10  | Esmaeili 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 | √ (GP) |    |    |    |    |    |
| 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 Bandwith 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 Overrpressure;

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 iterated 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   |     |    |    |    |    | √   |
| 4   | Jiang et al.                      | [105]| 2013 | Open pit GW dewatering           |     |    |    |    | √  |     |
| 5   | El-Ghandour & Elsaid              | [106]| 2013 | GW management                    |     |    |    |    |    | √   |
| 6   | Najafi et al.                     | [107]| 2015 | Out seam dilution LW coal mine   |     |    |    |    |    |     |
| 7   | Chang et al.                      | [108]| 2016 | Estimation of GWL                |     |    |    |    |    | √   |
| 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 |     |    |    |    |    | √   |
| 11  | Gholami et al.                    | [112]| 2017 | GW quality assessment            |     |    |    |    |    | √   |
| 12  | Fattahi et al.                    | [113]| 2018 | Dissolved metal level in ARD     |     |    |    |    |    |     |
| 13  | Jalalkamali and Jalalkamali       | [114]| 2018 | Prediction of GW quality indeces |     |    |    |    |    | √   |

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          |     |    |    |    |    | √   |
| 2   | Moharram et al.       | 116  | 2012 | Optimal GW management            |     |    |    |    |    |     |
| 3   | Jiang et al.          | 105  | 2013 | GW dewatering optimization       |     |    |    |    |    | √   |
| 4   | Safavi et al.         | 117  | 2013 | Optimal aquifer management       |     |    |    |    |    |     |
| 5   | Izquierdo et al.      | 118  | 2014 | DSS for mining solution spaces   |     |    |    |    |    | √   |
| 6   | Mohammadi et al.      | 119  | 2015 | CoG Optimization                 |     |    |    |    |    |     |
| 7   | Jang et al.           | 120  | 2015 | DSS for dilution ore loss        |     |    |    |    |    |     |
| 8   | Cetin & Dowd          | 121  | 2016 | CoG Optimization                 |     |    |    |    |    |     |
| 9   | Ahmadi et al.         | 122  | 2018 | CoG Optimization                 |     |    |    |    |    |     |

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