Application of Soft Computing Methods for the Estimation of Roadheader Performance from Schmidt Hammer Rebound Values

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Abstract

Estimation of roadheader performance is one of the main topics in determining the economics of underground excavation projects. The poor performance estimation of roadheader scan leads to costly contractual claims. In this paper, the application of soft computing methods for data analysis called adaptive neuro-fuzzy inference system- subtractive clustering method (ANFIS-SCM) and artificial neural network (ANN) optimized by hybrid particle swarm optimization and genetic algorithm (HPSOGA) to estimate roadheader performance is demonstrated. The data to show the applicability of these methods were collected from tunnels for Istanbul's sewage system, Turkey. Two estimation models based on ANFIS-SCM and ANN-HPSOGA were developed. In these models, Schmidt hammer rebound values and rock quality designation (RQD) were utilized as the input parameters, and net cutting rates constituted the output parameter. Various statistical performance indices were used to compare the performance of those estimation models. The results indicated that the ANFIS-SCM model has strong potentials to estimate roadheader performance with high degrees of accuracy and robustness.

1. INTRODUCTION

Roadheader is a mechanized excavation equipment used for excavating purposes in underground mining applications and civil tunnels. Based on its capabilities to cut virtually any tunnel profile, roadheaders have been steadily endorsed by civil construction contractors looking for ways to improve productivity and reduce costs [1]. Estimation of the excavation performance of roadheader for any geological formation is one of the main concerns in determining the economic aspects of a mechanized mining and/or tunneling operation. The performance analysis of roadheader machines plays an important role in the cost and time of underground completion; therefore, correct estimation of the roadheader performance has a key impact on the effective planning of the excavation project [2]. Factors affecting the excavation performance include: (i) cutting mode (overcutting, sumping, undercutting, traversing); (ii) rock mass properties (joints, fractures, bedding planes, fault zones); (iii) cutting tools (roller cutters, drag bits); (iv) intact rock properties (tensile strength, elasticity, abrasiveness, plasticity, uniaxial compressive strength (UCS), brittleness, hardness); (v) machine parameters (torque, machine weight, thrust and available power); (vi) size and shape of the opening; (vii) operational factors (support requirements, gradient, haulage capacity, water inflow); (viii) cutting geometry (cutting depth, angle of attack, spacing of the cutters, rake angle); and (ix) operator skills [3].

The estimation of roadheader performance is a highly complex task. Nevertheless, several researches are conducted to find a significant relationship between the roadheader performance and other parameters influencing it [4-11]. Researchers have also focused on developing performance estimation models for roadheaders. Sandbak [12] and Douglas [13] proposed a rock classification system that could be employed to explain the changes of roadheader advance rates at San Manuel Copper Mine in an inclined drift at an 11% grade. Bilgin and Seyrek [14] [15] and Ebrahimabadi and Azimipour [16] studied a roadheader performance model based on rock quality designation (RQD) and UCS. Fowel and Johnson [17] introduced a model in which three parameters of the swept area, cutter head advance, and rate per minute are applied to model the rate of the roadheader performance based on the results from simulation of excavating machines in the laboratory. Copur and Ozdemir [18] applied the data collected from a roadheader at Colorado School of Mine to predict the roadheader performance based on the three factors of the roadheader weight, cutterhead power, and roadheader penetration index. Bilgin and Dincer [19] studied some geological and geotechnical factors affecting the performance of a roadheader in an inclined tunnel. Ebrahimabadi and Goshtasbi [20] applied predictive models for roadheader's cutting performance in coal measure rocks. Ebrahimabadi and Goshtasbi [21] have also suggested a method to predict the performance of roadheaders based on the Rock Mass Brittleness Index. Abdolreza and Siamak [2] developed a model to predict roadheader performance using rock mass properties.

Although previous efforts are valuable but these empirical models are not capable of distinguishing the sophisticated structures involved in a dataset in many cases (Salsani and Daneshian [1]). This was a primary reason for seeking an improved model. To do this, already developed methods such as soft computing methods, which can successfully model the behavior of linear and nonlinear involved in data, can be useful. In this paper, the application of soft computing methods for data analysis called adaptive neuro-fuzzy inference system-subtractive clustering method (ANFIS-SCM) and artificial neural network (ANN) optimized by hybrid particle swarm optimization and genetic algorithm (HPSOGA) to estimate the roadheader performance is demonstrated. In these models, Schmidt hammer rebound values and rock quality designation (RQD) are utilized as the input parameters, and net cutting rates are output parameters. The data to show the applicability of these methods were collected from tunnels for Istanbul's sewage system, Turkey.

2. MATERIALS AND METHODS

2.1. Artificial neural network - hybrid particle swarm optimization and genetic algorithm

2.1.1. Artificial neural network

Artificial neural networks (ANNs) have appeared as a result of simulation of biological nervous systems, such as brain, on a computer. But biological neural networks are much more complicated than the mathematical models used for ANNs [22].

ANNs are parallel information processing methods that can express complex and nonlinear relationship use, number of input-output training patterns from the experimental data. ANNs provide a nonlinear mapping between inputs and outputs by their intrinsic abilities [23]. The success in obtaining a reliable and robust network strongly depends on the correct data preprocessing, appropriate architecture selection, and apt network training choice [24]. The ANN is trained by performing optimization of weights for each node interconnection and bias terms, until the output values at the output layer neurons are as close as possible to the actual outputs [25].

The ANN is usually divided into three parts as follows: the input layer, the hidden layer, and the output layer. The information included in the input layer is mapped to the output layers through the hidden layers. Each unit can only send its output to the units on the higher layer and receive its input from the lower layer. This structure is known as multilayer perceptron (MLP). More hidden layers can be added to obtain an entirely powerful multilayer network [22].

The data are split into two sets, a training data set and a validating data set. The model is produced using only the training data. The validating data are used to estimate the accuracy of the model performance. In training a network, the objective is to find an optimal set of weights [25].

2.1.2 Genetic algorithm

The genetic algorithm (GA) is a frequently used evolutionary computation technique. This method was originally developed by Holland John [26] and since then it has been successfully applied to various optimization problems. In the GA, a candidate solution for a particular problem is called an individual or a chromosome and consists of a linear list of genes [27-30].

The GA starts off with an initial population of randomly generated chromosomes. During successive iterations, named generations, the initial chromosomes advance towards stronger chromosomes by reproduction among candidate solutions of the previous generation. In the next step the binary strings are decoded and converted into optimization variable values, using linear scaling. The objective function is evaluated from the established optimization variable values and a measure of worth or fitness is evaluated. In the natural world, this would be an individual's ability to survive in their environment [27-30].

In the next step, the individuals with the highest fitness in the population are selected as parents and are coupled to breed new individuals for the next generation. In the final step, genetic operators are used to manipulate the characters (genes) of chromosomes directly, using the assumption that certain individual's gene codes, on average, produce fitter individuals. The genetic operators of GA include reproduction; crossover and mutation are used for the parents with certain probabilities to generate new individuals. The reproduction operator simply selects, in proportion to fitness, an individual and allows it to survive by copying it directly into the next generation. The crossover operator creates two new chromosomes from two existing chromosomes by randomly choosing a crossover point and exchanging the part of parents after this crossover point. The mutation operator produces new chromosomes by randomly changing the genes of existing chromosomes [27-30].

The fitness of the newly produced offspring is then evaluated using the same criterion, and the chromosomes in the current population are then replaced by their offspring according to a certain replacement strategy. Such a GA cycle is repeated until a set termination criterion is reached.

2.1.3 Particle swarm optimization

The particle swarm optimization (PSO) is a population-based stochastic optimization technique presented by Eberhart and Kennedy [31] in order to solve problems with continuous search spaces. PSO inspired by the social behavior of fish schooling or bird flocking. The algorithm works by initializing a flock of birds randomly over the searching space, where every bird is called a 'particle.' These 'particles' fly with a certain velocity and locate the best global position after some iteration. The position of each particle, xi, representing a particular solution of the problem, is used to compute the value of the fitness function to be optimized. Each particle may change its position and consequently may explore the solution space, simply varying its associated velocity. In fact, the main PSO operator is the velocity update, which considers the best position, in terms of fitness value reached by all the particles during their paths, , and the best position that the agent itself has reached during its search, , resulting in a migration of the entire swarm toward the global optimum [32].

The particle moves around according to its velocity and position at every iteration; the cost function to be optimized is evaluated for each particle in order to rank the current location. The position of each particle is updated using its velocity vector as shown in Eq. (2).

$$V_i^{t+1} = \omega V_i^t + C_1 r_1^t \left(P_i^t - X_i^t\right) + C_2 r_2^t \left(P_g^t - X_i^t\right) \quad (1)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (2)$$

where, is the velocity vector at iteration t, r1 and r_2 represents random numbers in the range [0,1]; denotes the best ever particle position of particle i, and corresponds to the best global position in the swarm up to iteration t. The remaining terms are problem-dependent parameters; for example, C_1 and C_2 represent "trust" parameters indicating how much confidence the current particle has in itself (C_1: cognitive parameter) and how much confidence it has in the swarm (C_2: social parameter), and ω is the inertia weight [29, 33, 34].

2.1.4 Hybrid genetic algorithm and particle swarm optimization

Although the GAs have been successfully used to a wide range of problems, using the GAs for large-scale optimization could be very expensive due to its requirement of a large number of function evaluations for convergence. This would result in a prohibitive cost for the computation of function evaluations even with the best computational facilities available today [35]. Considering the efficiency of the PSO and the compensatory property of the GA and the PSO, combining the searching abilities of both methods into a single algorithm seems to be a logical approach. In this paper, the hybrid HPSOGA, resulting from combining GA and PSO and originally presented by Juang [36], was administered.

2.2 Adaptive network-based fuzzy inference system

A fuzzy inference system can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Neural networks are information-processing programs inspired by mammalian brain processes. They are composed of a number of interconnected processing elements analogous to neurons. The training algorithm feeds a set of data inputs to the neural networks and checks their output results. Combining neural networks with fuzzy logic has been shown to reasonably emulate the human process of expert decision-making. In traditional neural networks, only weight values change during learning, thus the learning abilities of neural networks are combined with the inference mechanism of the fuzzy logic for a neuro-fuzzy decision-making system [37].

An adaptive neural network is a network structure consisting of several nodes interconnected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Once the fuzzy inference system is initialized, neural network algorithms can be utilized to determine the unknown parameters (premise and consequent parameters of the rules) minimizing the error measure, as conventionally defined for each of the system's variables. Due to this optimization procedure, the system is called adaptive [38].

The architecture of ANFIS consists of five layers. A brief introduction of the model follows.

Layer 1: Each node i in this layer generates a membership grade of a linguistic label. For instance, the node function of the i[th] node might be:

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-v_i}{\sigma_i}\right)^2\right]^{b_i}} \tag{3}$$

where, x is the input to node i, and Ai is the linguistic label (small, large, etc.) associated with this node; and $\{\sigma_i, V_i, b_i\}$ is the parameter set that changes the shapes of the MF. Parameters in this layer are referred to as the "premise parameters."

Layer 2: Each node in this layer calculates the "firing strength" of each rule via multiplication:

$$Q_i^2 = W_i = \mu_{Ai}(x).\mu_{Bi}(y) \quad i = 1,2 \tag{4}$$

Layer 3: The i[th] node of this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$Q_i^3 = \overline{W_i} = \frac{w_i}{\sum_{j=1}^{2} w_j}, \quad i = 1,2 \tag{5}$$

For convenience, outputs of this layer will be called "normalized firing" strengths.

Layer 4: Every node i in this layer is a node function:

$$Q_i^4 = \overline{W_i} f_i = \overline{W_i}(p_i x + q_i y + r_i) \tag{6}$$

where, $\overline{W_i}$ is the output of layer 3. Parameters in this layer will be referred to as "consequent parameters."

Layer 5: The single node in this layer is a circle node labeled R that computes the "overall output" as the summation of all incoming signals:

$$Q_i^5 = QverallOutput = \sum \overline{W_i} f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{7}$$

Also, in this study, subtractive clustering method (SCM) is utilized to identify the antecedent MFs.

2.2.1 Subtractive clustering method

The SCM as introduced by Chiu [39] features data points as the candidates for the center of clusters. The algorithm continues as follow:

At first a collection of n data points $\{X_1, X_2, X_3, ..., X_n\}$ in an M-dimensional space is considered. Since each data point is a candidate for a cluster center, a density measure at data point X_i is defined as:

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|x_i - x_j\|^2}{\left(\frac{r_a}{2}\right)^2}\right) \tag{8}$$

where, r_a is a positive constant. Therefore, a data point will have a high density value if it has many neighboring data points. The radius r_a defines a neighborhood; data points outside this radius contribute only slightly to the density measure. After the density measure of each data point has been calculated, the data point with the highest density measure is selected as the first cluster center. Let X_{c1} be the point selected and D_{c1} its density measure. Next, the density measure for each data point x_i is revised as follows:

$$D_i = D_i - D_{ci} \exp\left(-\frac{\|x_i - x_{ci}\|^2}{\left(\frac{r_a}{2}\right)^2}\right) \tag{9}$$

where, r_a is a positive constant. After the density calculation for each data point is revised, the next cluster center X_{c2} is selected and all of the density calculations for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated.

3. ESTIMATION OF ROADHEADER PERFORMANCE

3.1. Inputs and output data

Dataset applied in this study for determining the relationship between the set of input (Schmidt hammer rebound values and RQD) and output (net cutting rates of the roadheader for each zone) variables are gathered from open source literature [40, 41]. These data recorded previously during the construction of tunnels for Istanbul's sewage system have been evaluated. Schmidt hammer rebound values from 36 different rock zones were collected together with the net cutting rates of roadheader for each zone. Rebound tests were carried out with a Proceq N-type hammer. On any one rock type at least three sets of tests were conducted, depending on the geology of the encountered rock formations. At each test point 15–20 continuous rebound values were measured, and the suspected low values were excluded from the calculation of a mean value (R1-values) if they satisfied Chauvenet's criterion (Test Procedure 1). Test Procedure 2: Select the peak rebound value from five continuous impacts at a point and discard the remaining values (R2-values) [42]. Test Procedure 3: Select the peak rebound value from ten continuous impacts at a point and discard the remaining values (R3-values) [43]. The partial dataset used in this study is presents in Table 1. Also, descriptive statistics of all data sets are illustrated in Table 2.

Table 1. Partial dataset used in this study [40, 41].

Zone	Description of rock formation	Input parameters				Output parameter
		RQD (%)	R1-value	R2-value	R3-value	Net cutting rate (m^3/h)
1	Mudstone	0	29	31	32	25
2	Shale	0	35	35	43	20.4
3	Shale	23	37	34	44	20.4
4	Mudstone	0	38	36	45	16.2
5	Shale-Siltstone	19	38	36	46	20.3
6	Shale	19	31	30	34	23
7	Sandstone–Greywacke	0	48	45	49	23
8	Shale with Clay Hands	23	37	35	38	19.6
9	Shale with Clay Hands	19	38	41	45	18.4
10	Shale	33	47	45	50	21.4

Table 2. Statistical description of dataset utilized for the construction of the model.

Parameter	Min	Max	Average
RQD (%)	0	100	53.94
R1-value	29	63	49.78
R2-value	30	61	47.67
R3-value	32	64	51.75
Net cutting rate (m3/h)	2	25	11.39

3.2. Pre-processing of data

In data-driven system modeling methods, some pre-processing steps are commonly implemented prior to any calculations, to eliminate any outliers, missing values, or bad data. This step ensures that the raw data retrieved from a database is perfectly suitable for modeling. In order to soften the training procedure and improve the accuracy of prediction, all data samples are normalized to adapt to the interval [0, 1] according to the following linear mapping function:

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

where x is the original value from the dataset, x_M is the mapped value, and x_{min} (x_{max}) denotes the minimum (maximum) raw input values, respectively.

3.3. Estimation of roadheader performance using ANN-HPSOGA model

3.3.1. Tuning parameters for GA and PSO

To develop an accurate ANN model, the training and validation processes are important steps. In the training process, a set of input-output patterns is repeated to the ANN. From that, weights of all the interconnections between neurons are adjusted until the specified input yields the anticipated output. Through these activities, the ANN learns the correct input-output response behavior. The model training stage includes choosing a criterion of fit (mean squared error) and an iterative search algorithm to find the network parameters that minimizes the criterion. Hybridizing GA with PSO (HPSOGA) was used in an effort to formalize a systematic approach to training the ANN, and to insure the creation of a valid model. It was used to perform global search algorithms to update the weights and biases of the neural network. The control parameters used for running PSO and GA are shown in Tables 3 and 4 respectively.

Table 3. The control parameters used for running the PSO.

Parameter	Value
Number of population (swarm size)	100
Number of generations	1000
Personal learning coefficient	1.4962
Global learning coefficient	1.4962
Inertia weights	0.73
Fitness	Mean squared error

Table 4. The control parameters used for running the GA.

Parameter	*Value*
Number of population	*100*
Number of generations	*1000*
Crossover probability	*0.7*
Mutation probability	*0.2*
Selection function	*Ranking*
Fitness	*Mean squared error*

3.3.2. Network architecture

Architecture of the ANN model includes the type of network, number of input and output neurons, transfer function, number of hidden layers as well as number of hidden neurons. Generally, the input neurons and output neurons are problem specific ([44]). In this paper, multi-input single-output structure had been utilized; therefore, there will be only one output neuron. ANN-HPSOGA model was utilized to create a prediction model for the estimation of roadheader performance from available data, using MATLAB environment. Fig. 1 shows the architecture of ANN-HPSOGA model for the estimation of roadheader performance. As it can be seen in Fig.1, R1-values, R2-values, R3-values and RQD were defined as input parameters into the ANN-HPSOGA model and the net cutting rate as output. A dataset that included 36 data points was employed in the current study, while 27 data points (75%) were utilized for constructing the model and the remainder data points (i.e. 9 data points) were utilized for assessment of degree of accuracy and robustness.

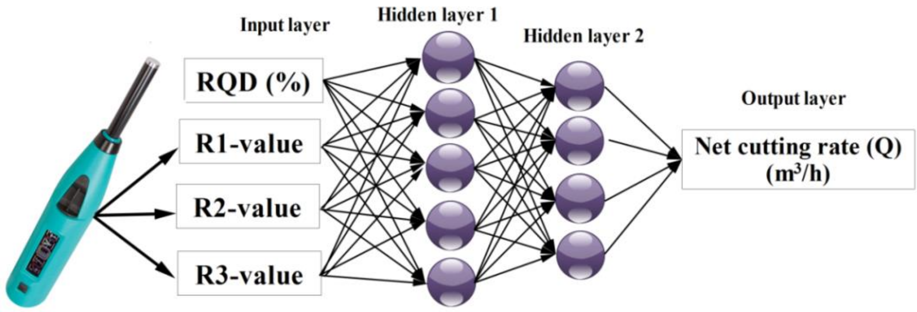


Figure 1. The architecture of ANN-HPSOGA model.

Also, it is important that the transfer function possesses the properties of differentiability and continuity. Generally, log sigmoid function is utilized in the hidden layer and the output generated has a value between 0 and 1 however, the linear transfer function is more suitable in output [44]. The equations for the log and linear transfer functions used in this study are shown in Eqs. (11) and (12):

$$f(x) = \frac{1}{1+\exp(-x)} \tag{11}$$

$$f(x) = x \tag{12}$$

3.4. Estimation of roadheader performance using ANFIS-SCM model

In a conventional fuzzy inference system, the number of rules is decided by an expert who is familiar with the target system to be modeled. In ANFIS simulation, however, no expert is available and the number of membership functions (MFs) assigned to each input variable is chosen empirically, that is, by plotting the data sets and examining them visually, or simply by trial and error. For data sets with more than three inputs, visualization techniques are not very effective and it often relies on trial and error. Generally, it becomes very difficult to describe the rules manually in order to reach the precision required with the minimized number of membership functions (MFs), when the number of rules are larger than 3. Therefore, an automatic model identification method becomes a must, which is often realized by means of a training set of input-output pairs (Jang 1993; Jang et al. 1997; [45, 46]).

The SCM is an attractive approach to the synthesis of ANFIS networks, which estimates the cluster number and its cluster location automatically. In subtractive clustering algorithm, each sample point is seen as a potential cluster center. By using this approach computation time becomes linearly proportionate to data size yet reamins independent of the dimension problem under consideration ([45, 47-49]).

Fig. 2 shows the fuzzy architecture of ANFIS-SCM model for the estimation of roadheader performance. The specifications of the ANFIS-SCM model are illustrated in Table 5.

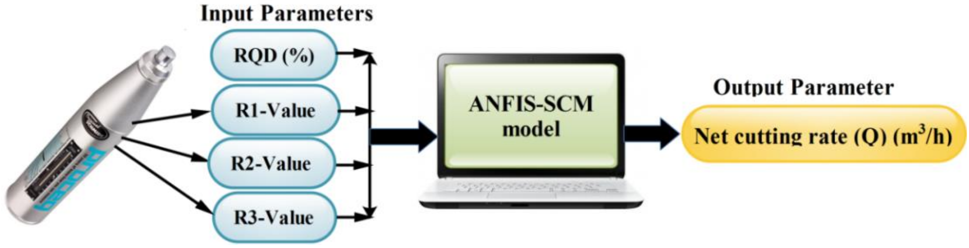


Figure 2. The architecture of ANFIS-SCM model.

Table 5. Specifications of the ANFIS-SCM model.

Parameter	Description
Membership function type	Gaussian
Output membership function	Linear
Number of nodes	275
Number of linear parameters	135
Number of nonlinear parameters	216
Total number of parameters	351
Number of training data pairs	27
Number of testing data pairs	9
Number of fuzzy rules	27

By using the SCM, the cluster center of all data was determined. Then, the numbers of subtractive centers were utilized to generate automatic MFs and rule base as well as the location of MF within dimensions. Fig. 3 shows the membership functions of the input parameters for ANFIS-SCM model. The numbers of rules achieved for the ANFIS-SCM model are 27.

4. MODELS PERFORMANCE EVALUATION

4.1. Performance criteria

To evaluate the performances of the ANFIS-SCM and ANN-HPSOGA models, root-mean-squared-error (RMSE), mean squared error (MSE), and squared correlation coefficient (R2) were chosen to be the measure of accuracy. N is the number of samples, y and y' are the measured and predicted values, respectively. RMSE, MSE and R2 could be defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i^{'}\right)^2} \qquad (13)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - y_i^{'}\right)^2 \qquad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i - y_i^{'}\right)^2}{\sum_{i=1}^{N} y_i^2 - \frac{\sum_{i=1}^{N} y_i^{'2}}{N}} \qquad (15)$$

where $\mu_y\,(\mu_{y^{'}})$ denotes the mean value of the $y(y'), k = 1,\ldots,N$.

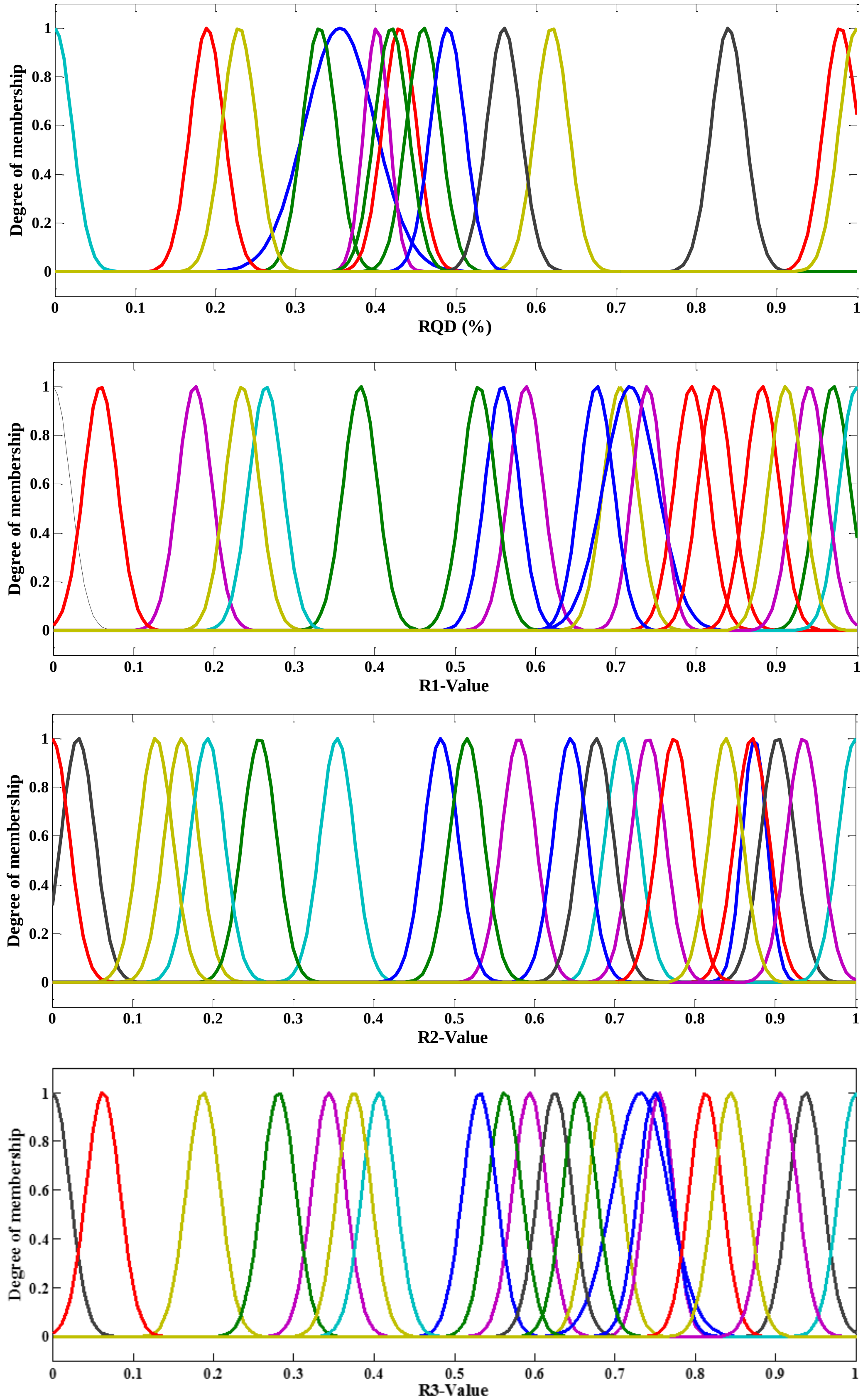


Figure 3. Membership functions of the ANFIS-SCM model.

4.2. Training and validation models

A comparison between the results of ANFIS-SCM and ANN-HPSOGA models is shown in Table 6. As it can be observed from this table, the ANFIS-SCM model with RMSE=0.095, MSE=0.009 and R2=0.83 for testing datasets performs better than the ANN-HPSOGA model for estimating roadheader performance.

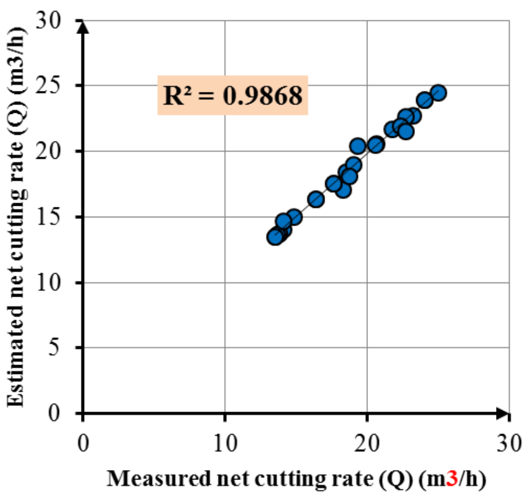
Table 6. A comparison between the results of ANFIS-SCM and ANN-HPSOGA models for training and testing datasets.

Model		*RMSE*	*MSE*	*R^2*
ANFIS-SCM	*Training datasets*	*0.039*	*0.0015*	*0.98*
	Testing datasets	*0.095*	*0.009*	*0.83*
ANN-HPSOGA	*Training datasets*	*0.167*	*0.028*	*0.94*
	Testing datasets	*0.241*	*0.058*	*0.81*

The obtained RMSE, MSE and R2 values for training datasets indicate the capability of learning the structure of data samples, whereas the results of testing dataset reveal the generalization potential and the robustness of the system modeling methods.

Furthermore, a correlation between the estimated values of net cutting rate by ANFIS-SCM and ANN-HPSOGA models and measured values for 36 data sets at training and testing phases is shown in Figs. 4 and 5.

Also, a comparison between estimated values of net cutting rate by ANFIS-SCM and ANN-HPSOGA models and measured values for 36 data sets at training and testing phases is shown in Figs. 6 and 7. The results of the ANFIS-SCM model in comparison with actual data shows the precision of ANFIS-SCM model.



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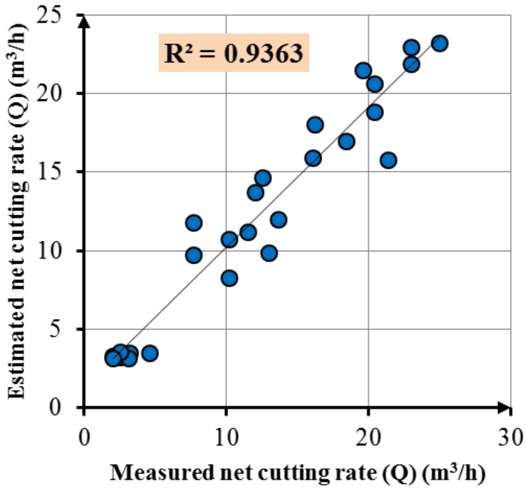
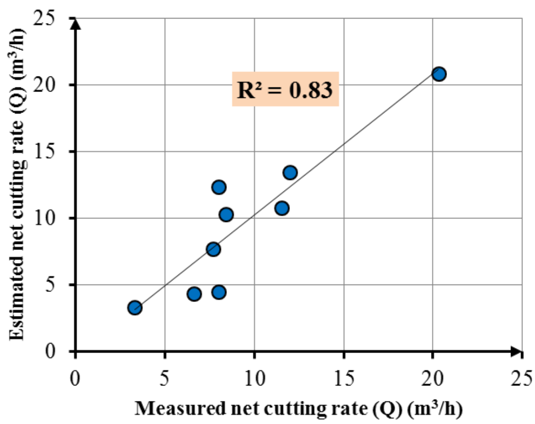


(b)

Figure 4. Correlation between measured and estimated net cutting rates for training datasets, a) ANFIS-SCM model, b) ANN-HPSOGA model



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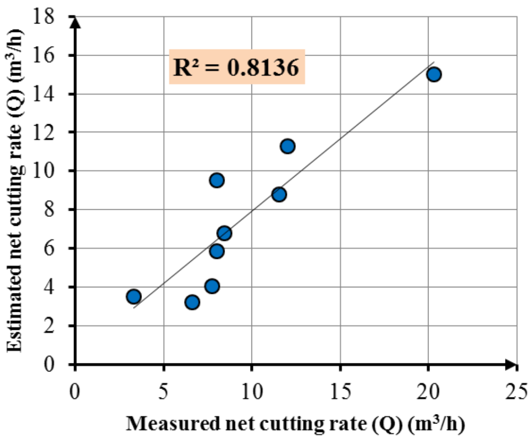
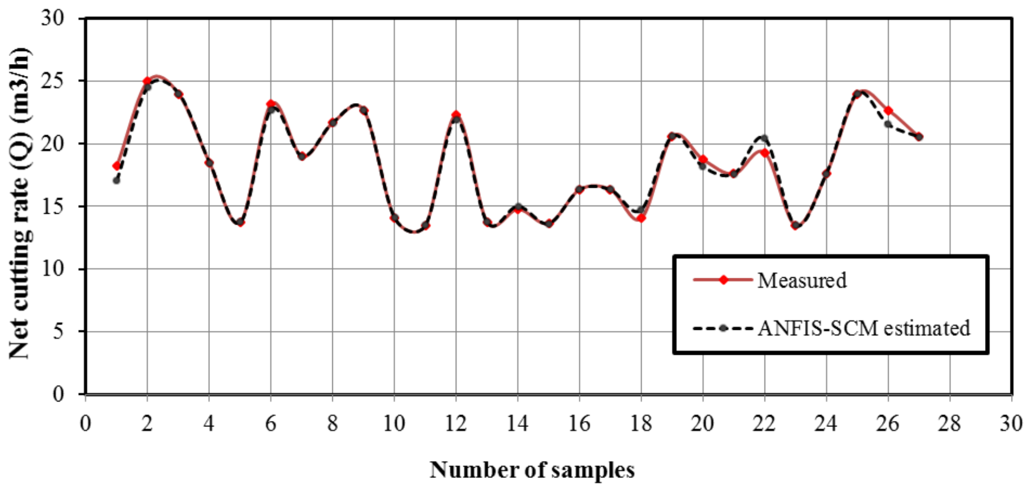


(b)

Figure 5. Correlation between measured and estimated net cutting rate for testing datasets, a) ANFIS-SCM model, b) ANN-HPSOGA model

5. CONCLUSIONS

Estimation of the excavation performance of roadheader for any geological formation is one of the main concerns in determining the economic aspects of a mechanized mining and/or tunneling operation. The performance analysis of roadheader machines plays an important role in the required cost and time of underground completion; therfore, correct estimation of the roadheader performance is a significant determinant in the effective planning of the excavating project. In this field, several studies have been conducted to find a significant relationship between the roadheader performance and other parameters influencing its performance.



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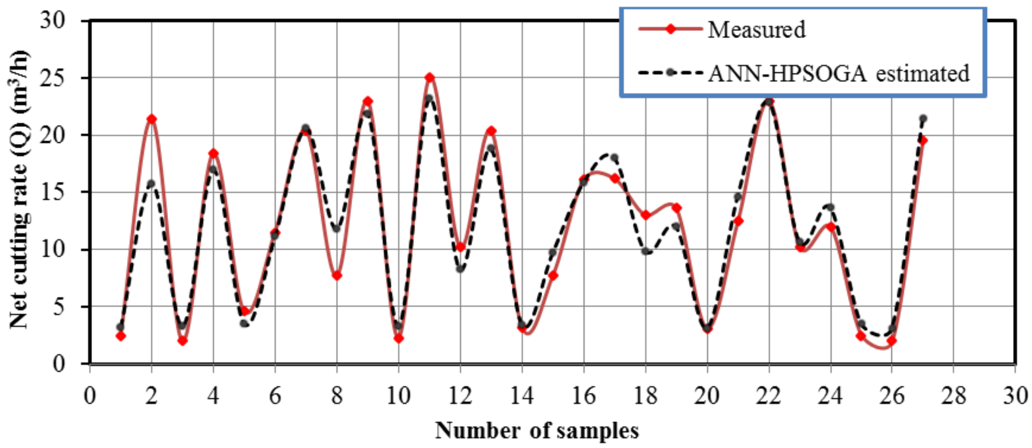
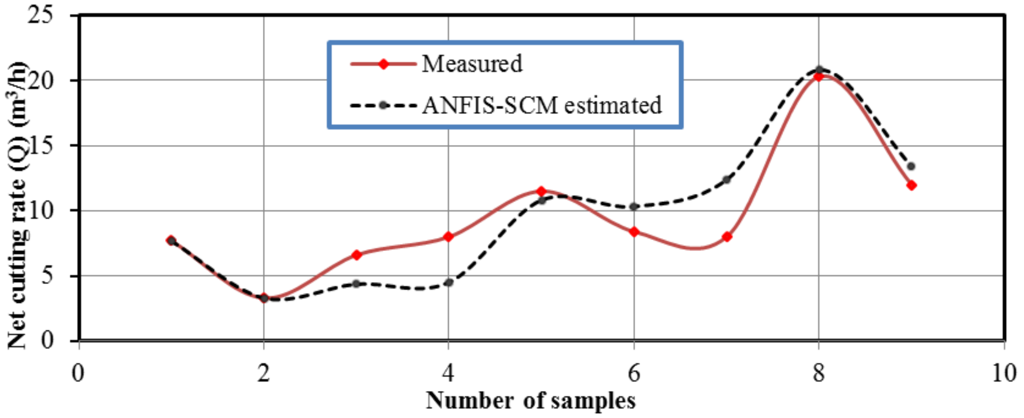


Figure 6. Comparison between measured and estimated net cutting rates for training datasets, a) ANFIS-SCM model, b) ANN-HPSOGA model



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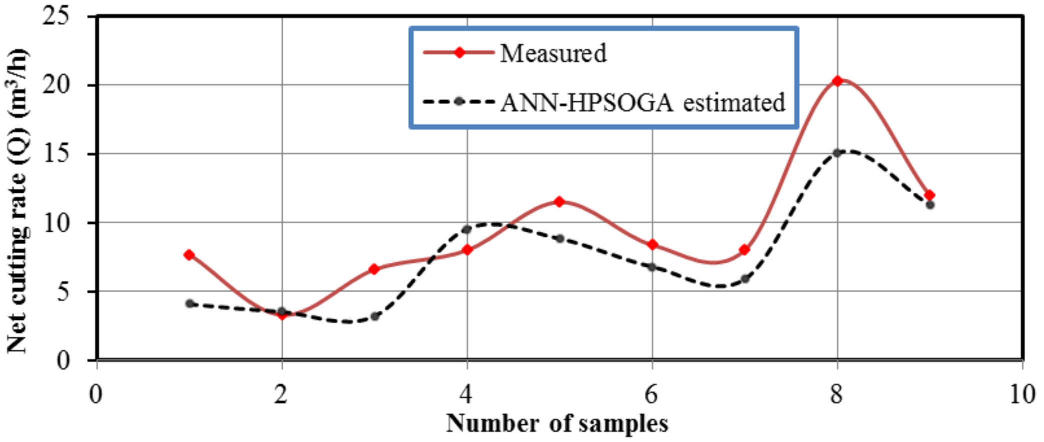

(b)

Figure 7. A comparison between measured and estimated net cutting rates for testing datasets, a) ANFIS-SCM model, b) ANN-HPSOGA model

Although previous efforts are valuable, these empirical models are not capable of distinguishing the sophisticated structures involved in a dataset. For doing the purpose, utilize of developed methods such as soft computing methods, which can successfully model the behavior of linear and nonlinear involved in data, is useful. In this paper, the application of soft computing methods for data analysis called adaptive neuro-fuzzy inference system- subtractive clustering method (ANFIS-SCM) and artificial neural network (ANN) optimized by hybrid particl swar optimization and genetic algorithm (HPSOGA) to estimate roadheader performance is demonstrated. In these models, Schmidt hammer rebound values and rock quality designation (RQD) were utilized as the input parameters, and net cutting rates constituted the output parameter.

It was concluded that,

- Implementation hybrid the particle swarm optimization and genetic algorithm (HPSOGA) as an optimizer of connection weights of artificial neural network to estimate the roadheader performance was demonstrated in detail.

- The HPSOGA has high robustness in optimization issue due to integrating global and local search abilities of GA and PSO. The results showed that it can be used to tune the weights of ANN model for the assessment of roadheader performance.

- A comparison was made between ANFIS-SCM and ANN-HPSOGA models, using 36 data samples, and based on the performance indices RMSE, MSE and R2, ANFIS-SCM with RMSE=0.095, MSE=0.009 and R2=0.83 was selected as the best predictive model.

- Consequently, it may be concluded that ANFIS-SCM is a reliable system modeling technique for estimating roadheader performance with a highly acceptable degree of accuracy and robustness.

- This study shows that the ANFIS-SCM and ANN-HPSOGA approaches can be used as powerful tools for modeling some problems involved in mining engineering.

REFERENCES

1. Salsani, A., et al., Predicting roadheader performance by using artificial neural network. Neural Computing and Applications, 2014. **24**(7-8): p. 1823-1831.

2. Abdolreza, Y.-C., et al., A new model to predict roadheader performance using rock mass properties. Journal of Coal Science and Engineering (China), 2013. **19**(1): p. 51-56.

3. Iphar, M., ANN and ANFIS performance prediction models for hydraulic impact hammers. Tunnelling and Underground Space Technology, 2012. **27**(1): p. 23-29.

4. Uehigashi, K., et al. Possibility of rock excavation by boom-type tunneling machines. 6th Australian Tunneling Conference. Melbourne1987. p. 253–259.

5. Schneider, H., Criteria for selecting a boom-type roadheader: Min MagSept 1988, P183–187. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 1989. **26**(2): p. 78-79.

6. Gehring, K. H., A cutting comparison. Tunnels and Tunnelling, 1989. **21**: p. 27-30.

7. Rostami, J., et al. Performance prediction: a key issue in mechanical hard rock mining. International Journal of Rock Mechanics and Mining Science & Geomechanics Abstracts1995. p. 171A-171A.

8. Thuro, K., et al., Predicting roadheader advance rates. Tunnels & Tunnelling International, 1999. **6**: p. 36-39.

9. Tumac, D., et al., Estimation of rock cuttability from shore hardness and compressive strength properties. Rock Mechanics and Rock Engineering, 2007. **40**(5): p. 477-490.

10. Madan, M. Underground excavation with road headerscase studies. World Tunnel Congress2008. p. 1073-1084.

11. Goshtasbi, K., et al., Evaluation of boring machine performance with special reference to geomechanical characteristics. International Journal of Minerals, Metallurgy and Materials, 2009. **16**(6): p. 615-619.

12. Sandbak, L. A. Road header drift excavation and geotechnical rock classification at San Manuel, Arizona. Proceedings of the Rapid Excavation and Tunnelling Conference. New York1985. p. 902–916.

13. Douglas, W., Roadheaders open new horizons at San Manuel. Engineering & Mining Journal, 1985. **186**(8): p. 22-25.

14. Bilgin, N., ., et al., Roadheader performance in Istanbul, Golden Horn clean-up contributes valuable data. Tunnels & Tunneling, 1988. **6**: p. 41-44.

15. Bilgin, N., ., et al., Roadheaders clean valuable tips for Istanbul Metro. Tunnels & Tunneling, 1990. **10**: p. 29-32.

16. Ebrahimabadi, A., et al., Prediction of roadheaders' performance using artificial neural network approaches (MLP and KOSFM). Journal of Rock Mechanics and Geotechnical Engineering, 2015. **7**(5): p. 573-583.

17. Fowel, R. J., et al. Cuttability assessment applied to drag tool tunnelling machines. Proceeding of the 7th International Congress on Rock Mechanics, ISRM. Aachen.

18. Copur, H., et al., Roadheader applications in mining and tunneling industries. Mining Engineering, 1998. **50**: p. 38-42.

19. Bilgin, N., et al., Some geological and geotechnical factors affecting the performance of a roadheader in an inclined tunnel. Tunnelling and Underground Space Technology, 2004. **19**(6): p. 629-636.

20. Ebrahimabadi, A., et al., Predictive models for roadheaders’ cutting performance in coal measure rocks. Yerbilimleri, 2011. **32**(2): p. 89-104.

21. Ebrahimabadi, A., et al., A model to predict the performance of roadheaders based on the Rock Mass Brittleness Index. South African Institute of Mining and Metallurgy Journal, 2011. **111**(5): p. 355-364.

22. Khalaj, G., et al., Artificial neural network to predict the effect of heat treatments on Vickers microhardness of low-carbon Nb microalloyed steels. Neural Computing and Applications, 2013. **22**(5): p. 879-888.

23. Hornik, K., et al., Universal approximation of an unknown mapping and its derivatives using multilayer feedforward networks. Neural Networks, 1990. **3**(5): p. 551-560.

24. García-Pedrajas, N., et al., COVNET: a cooperative coevolutionary model for evolving artificial neural networks. IEEE Transactions on Neural Networks, 2003. **14**(3): p. 575-596.

25. Ahmadi, M. H., et al., Prediction of power in solar stirling heat engine by using neural network based on hybrid genetic algorithm and particle swarm optimization. Neural Computing and Applications, 2013. **22**(6): p. 1141-1150.

26. Holland John, H. Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence: MIT Press Cambridge, MA, USA, 1975.

27. Wang, C., et al., Identification of dynamic rock properties using a genetic algorithm. International Journal of Rock Mechanics and Mining Sciences, 2004. **41**: p. 490-495.

28. Osman, M., et al., A combined genetic algorithm-fuzzy logic controller (GA–FLC) in nonlinear programming. Applied Mathematics and Computation, 2005. **170**(2): p. 821-840.

29. Hassan, R., et al. A comparison of particle swarm optimization and the genetic algorithm. Proceedings of the 1st AIAA multidisciplinary design optimization specialist conference2005. p. 18-21.

30. Majdi, A., et al., Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses. International Journal of Rock Mechanics and Mining Sciences, 2010. **47**(2): p. 246-253.

31. Eberhart, R., et al. A new optimizer using particle swarm theory. Micro Machine and Human Science, 1995 MHS'95, Proceedings of the Sixth International Symposium on: IEEE, 1995. p. 39-43.

32. Chen, S.-F. Redundant Feature Selection Based on Hybrid GA and BPSO. Communication Software and Networks (ICCSN), 2011 IEEE 3rd International Conference on: IEEE, 2011. p. 414-418.

33. Shi, Y., et al. A modified particle swarm optimizer. Evolutionary Computation Proceedings, IEEE World Congress on Computational Intelligence: IEEE, 1998. p. 69-73.

34. Fattahi, H., Application of improved support vector regression model for prediction of deformation modulus of a rock mass. Engineering with Computers, 2016. **32**(4): p. 567-580.

35. Kaveh, A., et al., Hybrid genetic algorithm and particle swarm optimization for the force method-based simultaneous analysis and design. Iranian Journal of Science and Technology, Transaction B: Engineering, 2010. **34**(B1): p. 15-34.

36. Juang, C.-F., A hybrid of genetic algorithm and particle swarm optimization for recurrent network design. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 2004. **34**(2): p. 997-1006.

37. Fattahi, H., Indirect estimation of deformation modulus of an in situ rock mass: an ANFIS model based on grid partitioning, fuzzy c-means clustering and subtractive clustering. Geosciences Journal, 2016. **20**(5): p. 681-690.

38. Fattahi, H., Applying soft computing methods to predict the uniaxial compressive strength of rocks from schmidt hammer rebound values. Computational Geosciences, 2017. **21**(4): p. 665-681.

39. Chiu, S. L., Fuzzy model identification based on cluster estimation. Journal of intelligent and Fuzzy systems, 1994. **2**(3): p. 267-278.

40. Shahriar, K., Rock cuttability and geotechnical factors affecting the penetration rates of roadheaders. Ph D Thesis, Istanbul Technical University, 1988. p. 241.

41. Goktan, R., et al., A comparative study of Schmidt hammer testing procedures with reference to rock cutting machine performance prediction. International Journal of Rock Mechanics and Mining Sciences, 2005. **42**(3): p. 466-472.

42. Poole, R., et al., Consistency and repeatability of Schmidt hammer rebound data during field testing. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 1980. **17**(3): p. 167-171.

43. Hucka, V., A rapid method of determining the strength of rocks in situ. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 1965. **2**(2): p. 127-134.

44. Braik, M., et al. A comparison between GAs and PSO in training ANN to model the TE chemical process reactor. Proceedings of the AISB 2008 symposium on swarm intelligence algorithms and applications. p. 24-30.

45. Chopra, S., et al., Reduction of fuzzy rules and membership functions and its application to fuzzy PI and PD type controllers. International Journal of Control, Automation and Systems, 2006. **4**(4): p. 438.

46. Ming-bao, P., et al. Traffic flow prediction of chaos time series by using subtractive clustering for fuzzy neural network modeling. Intelligent Information Technology Application, 2008 IITA'08 Second International Symposium on: IEEE, 2008. p. 23-27.

47. Karimpouli, S., et al., Estimation of P-and S-wave impedances using Bayesian inversion and

adaptive neuro-fuzzy inference system from a carbonate reservoir in Iran. Neural Computing and Applications, 2016. p. 1-14.

48. Fattahi, H., et al., Hybrid ANFIS with ant colony optimization algorithm for prediction of shear wave velocity from a carbonate reservoir in Iran. Int Journal of Mining & Geo-Engineering, 2016. **50**(2): p. 231-238.

49. Fattahi, H., et al., Prediction of porosity and water saturation using pre-stack seismic attributes: a comparison of Bayesian inversion and computational intelligence methods. Computational Geosciences, 2016. **20**(5): p. 1075-1094.