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Applying improved artificial neural network models to evaluate drilling rate index

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ABSTRACT

The drilling rate index (DRI) is the most important input parameter of a commonly used performance prediction model for drilling and rock excavation. In this paper, the hybrid artificial neural network (ANN) with back propagation (BP) algorithm, simulated annealing algorithm (SAA), firefly algorithm (FA), invasive weed optimization algorithm (IWO) and shuffled frog leaping algorithm (SFLA) were used to build a prediction model for the indirect estimation of DRI. The estimation abilities offered using five ANN models (ANN-BP, ANN-SAA, ANN-FA, ANN-IWO and ANN-SFLA) were presented by using available data given in open source literature. In these models, strengths (Uniaxial Compressive Strength (UCS) and Brazilian Tensile Strength (BTS)) and indexes properties (Shore Scleroscope Hardness (SSH), diametral point load strength index ($Is_{(50)}\rightarrow$) and axial point load strength index ($Is_{(50)}\downarrow$)) were utilized as the input parameters, while the DRI was the output parameter. Various statistical performance indexes were utilized to compare the performance of those estimation models. The comparative results revealed that hybrid of SAA and ANN yield robust model which outperform other models in term of higher squared correlation coefficient (R^2), variance account for (VAF) and lower mean square error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE).

1. Introduction

Accurate prediction of drillability that defined as the rate of penetration have been one of the most important issues in planning, design and construction underground spaces and related projects over the past years. For example, rate of penetration of tunneling boring machine (TBM) has been studied by many researchers (Fattahi, 2016; Gholamnejad and Tayarani, 2010; Grima et al., 2000; Hassanpour et al., 2016; Kahraman, 2002; Mahdevari et al., 2014; Mohammadi et al., 2015; Salimi and Esmaeili, 2013; Yagiz et al., 2009; Yagiz and Karahan, 2011, 2015). Numerous factors affect the drillability of rocks. These factors can be divided into two parts: the first is the controllable parameters and the second is the uncontrollable parameters. Bit type and diameter, rotational speed, thrust, blow frequency and flushing are the controllable parameters. On the other hand the parameters such as rock properties and geological conditions are the uncontrollable parameters (Yarali and Kahraman, 2011). In some studies has been conducted so far the drillability was indicated and determining the rock factor or other indices was the goal; For example, drilling parameters (Akin and Karpuz, 2008) and lithological classification (Bahrampour et al., 2014; Tanaino, 2005). Assessment of the relationship between physical parameters of rock and drilling performance has been the subject of much research (Altindag, 2004, 2010; Ataei et al., 2015; Hoseinie et al., 2012; Li et al., 2016). Several previous investigators described uniaxial compressive strength (UCS) as the most important parameter to affect a drillability of rock (Akün and Karpuz, 2005; Aleman, 1981; Kahraman, 1999; Kahraman et al., 2003a; Poole and Farmer, 1978). Other important mechanical factors are Brazilian tensile strength (BTS) and Schmidt hardness index (Hosseini et al., 2014; Servet et al., 2014). Some geological factors such as the weathering, water table and quartz content are studied as factors in drillability performance (Benardos and Kaliampakos, 2004; Cheniany et al., 2012; Khademi Hamidi et al., 2010; Saeidi et al., 2013). In this regard, drilling rate index (DRI) proposed by Selmer-Olsen and Lien (1960). There are studies that concentrated on the correlation between DRI and physical properties of rock that have used regression analysis (Dahl et al., 2012; Yarali and Soyer, 2011, 2013). Although previous efforts are enormously valuable but in many cases, the aforesaid empirical models are not capable of distinguishing the sophisticated structures involved in the dataset. This reason has been the main cause of interest to better find out the interaction between DRI and other parameters and to propose a more precise and sure model for the estimation of the DRI (Khandelwal and Armaghani, 2016; Shafique and Bakar, 2015). For doing the purpose, computational intelligence methods are feasible,

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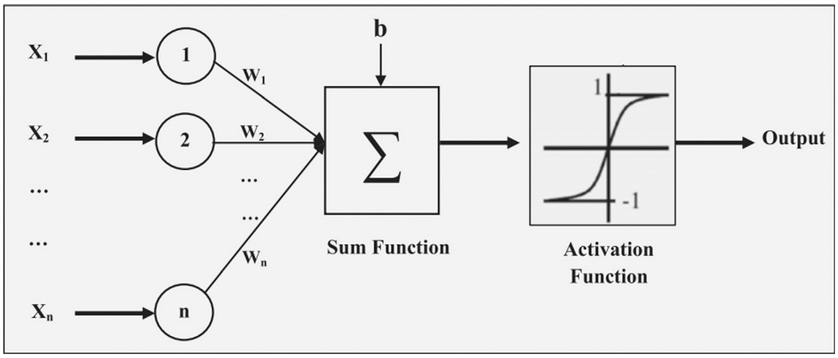

Fig. 1. A schematic representation of an MLP neural network.

quick and promising tools for the solving of engineering problems, particularly when the contact natures between independent variables and dependent variables are unknown (Armaghani et al., 2014; Asadi et al., 2013; Atici, 2011; Rezaei et al., 2014; Yesiloglu-Gultekin et al., 2013; Yilmaz and Yuksek, 2009).

ANN training has traditionally been carried out using a BP algorithm (ANN-BP model). However, this approach has some drawbacks, such as local minimum trapping, over-fitting, and weight interference, which have complicated ANN training. In contrast, the optimization algorithms have balanced exploration and exploitation capabilities; therefore, it does not get stuck in local minima (Togan, 2013; Toğan, 2012; Uzlu et al., 2014). In this study, improved ANN models are proposed for indirect prediction of DRI. Optimization implementation increases the efficiency of ANN model. Optimization algorithm in which employed for improving ANN efficiency are with simulated annealing algorithm (SAA), firefly algorithm (FA), invasive weed optimization algorithm (IWO) and shuffled frog leaping algorithm (SFLA). Finally, a statistical error analysis has been performed on the modeling results to investigate the feasibility and effectiveness of the proposed method.

2. A brief review of methods used in this study

In this section, first the literature review relevant to the ANN is presented and then, there are some descriptions about the optimization algorithms.

2.1. Artificial neural network (ANN)

Artificial neural networks (ANNs) are parallel information processing methods, which can express nonlinear relationship and complex use number of input–output training patterns from the experimental data. ANNs provide a nonlinear mapping between outputs and inputs by its intrinsic ability (Ahmadi et al., 2013; Hornik et al., 1989). The success in obtaining a reliable and robust network depends on the correct data preprocessing, correct architecture selection, and correct network training choice powerfully (García-Pedrajas et al., 2003). Multilayer perceptron (MLP) network (Cybenko, 1989) is the most well-known class of ANNs. MLPs have feed-forward architectures (Fig. 1). They are essentially capable of approximating any continuous function to an arbitrary degree of accuracy (Cybenko, 1989). These networks are usually applied to perform supervised learning tasks, which involve iterative training methods to adjust the connection weights within the network [33]. They are usually trained with back-propagation (BP) algorithm (Hajihassani et al., 2015, 2014; Tiryaki, 2008).

2.2. BP algorithm

The BP neural network developed by Rumelhart et al. (1986) is the most representative learning model for ANNs (Ediger and Akar, 2007; Nourani et al., 2012; Uzlu et al., 2014; Yan et al., 2008). In training by BP, the output error is reduced by adjusting the connection weights. Initially, the network runs with connection weights that are selected randomly. Within a feed forward- BP algorithm, all signals transmitted between the input and output layers. Finally, a desired output is computed by the network and the difference between the actual outputs and the desired one is computed. The network error is recognized as a difference between the actual and desired values. The individual weights are updated through back propagating the calculated error. This procedure is iterated to reduce the error (Simpson, 1991). The scenario for the p^{th} pattern in a feed forward-BP algorithm is presented in the following steps.

1. The i^{th} neuron holds a value of x_{pi} for the p^{th} pattern in input layer.
2. Net input to the j^{th} neuron for pattern p in hidden layer is:

$$net_{pj} = \sum_{i}^{N} W_{ij} O_{pi} \tag{1}$$

where W_{ij} is the weight from neuron i to j. The threshold function (f_j) is the output from each unit j. In this MLP f_j is sigmoid function as follow:

$$f(net) = \frac{1}{(1+e^{-Knet})}; \ (0 < f(net) < 1) \tag{2}$$

where k controls the function spread.

3. Output of the j^{th} neuron in the hidden layer is formulated as:

$$O_{pj} = f_j(net_{pj}) \tag{3}$$

4. Net input to the k^{th} neuron of the output layer is:

$$net_k = \sum_{j}^{N} W_{kj} X_{pj} \tag{4}$$

in which the weight value between the i^{th} hidden layer and the k^{th} output layer is W_{kj}.

5. The output of the k^{th} neuron of the output layer is:

$$O_{pk} = f_k(net_k) \tag{5}$$

6. E_p is the error function for a pattern p.

$$E_p = \frac{1}{2} \sum_{k}^{N} (t_{pk} - O_{pk})^2 \tag{6}$$

where t_{pk} and o_{pk}, respectively, are the target and actual outputs for pattern p on node k.

2.3. Simulated annealing algorithm (SAA)

SA is a general stochastic search algorithm used for solving several types of optimization problems with nonlinear functions and multiple