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Indirect measure of thermal conductivity of rocks through adaptive neuro-fuzzy inference system and multivariate regression analysis

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ABSTRACT

Thermal conductivity is an important property of rocks which is considered for energy-efficient building construction. This paper is aimed to predict the thermal conductivity of rocks utilizing the adaptive neuro-fuzzy inference system (ANFIS) and multivariate regression (MVR) analysis. In this regard, 44 datasets including the most effective parameters on thermal conductivity of rocks were collected from the literature. The physico-mechanical properties of rocks including uniaxial compressive strength, P-wave velocity, bulk density and porosity were used to develop the predictive models. The correlation of determination equal to 0.99 and 0.95 were obtained by ANFIS and MVR models respectively. The obtained results suggest that the ANFIS model outperforms the MVR model and is an applicable tool to predict thermal conductivity of rocks with high degree of accuracy.

1. Introduction

Thermal conductivity (TC) of rocks is an important part of their properties especially when the energy conservation is considered. The energy usage in a building is reduced when natural rocks with low TC are used in building construction [1,2]. Therefore, considering this property of rocks for the countries that excessively use heating or cooling systems is essential. Three different parameters including thermal diffusivity (TD), heat capacity (HC) as well as TC describe the rock thermal properties [3]. TD shows the areas of rock which have been influenced by the heat in each second. HC shows the rock capacity to heat accumulation where TC reveals the heat transmission capability of rocks. According to Verma [4], thermal stresses are induced by changing in the temperature which cause thermal strains in rocks. The TC of rocks is influenced by the rock type, moisture content, P-wave velocity and porosity. In Addition, mineral composition and crystallization of a rock influence its TC [5–7].

The TC of a construction material is usually determined through the hot plate steady-state method [8]. The TC of a rock is obtained by measuring the temperature gradients and heat input [9]. The TC of a rock might be obtained using the laboratory experiments or in the field under in-situ condition [10] and can be determined through the Fourier's law as follows:

$$\lambda = \frac{Qh}{A\Delta Tt} \quad (1)$$

in which λ represents the TC (W/m K), Q is the heat flow, h is rock thickness in the direction of heating (m) and A is the area of heated surface (m^2). ΔT is temperature difference between surface of material (°C) and t is heating time (h).

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The thermal conductivity of construction materials has been investigated by several researchers. Özkahraman et al. [2] conducted several laboratory tests to obtain the TC of various rocks. They investigated the relationships between the physical and mechanical characteristics of rocks including porosity, P-wave velocity, compressive strength and density. Finally, they resulted that P-wave velocity yields the best correlation among all characteristics and proposed a relationship between this property and TC. Yaşar et al. [1] collected various rock samples from different part of Turkey and conducted several laboratory tests on the collected samples. Finally, using the statistical analysis, they established several relationships to assess the TC of rocks using their mechanical and physical properties.

Recently, artificial intelligence (AI) methods have been widely used in many fields of science and engineering [11–14]. This is due to the ability of these methods for generating the non-linear relationships between input and output parameters. Singh et al. [15] and Khandelwal [16] employed artificial intelligence (AI) approaches to predict TC of rocks using simple rock parameters. They concluded that these methods are able to predict TC of rocks with good accuracy.

This paper presents an ANFIS model to predict TC of rocks based on their physical and mechanical properties. In this regard, a database consisting of 44 dataset was collected from the literature [1,2,15]. For the sake of comparison, the predicted results by proposed ANFIS model were compared with those of multivariate regression (MVR) analysis.

2. Adaptive neuro fuzzy inference system

Adaptive neuro-fuzzy inference system (ANFIS) developed by Jang [17] based on the Takagi–Sugeno [18] fuzzy inference system (FIS). ANFIS is a universal predictor with the capability to approximate any real continuous functions [19]. ANFIS works based on the construction of a set of if-then fuzzy rules with proper membership functions to produce the required output data. In general, a FIS is generated based on five functioning blocks including: several if-then fuzzy rules, a database to define the membership functions, a decision-making element to conduct the inference operations on the rules, a fuzzification interface to convert the inputs utilizing linguistic values and finally, a defuzzification interface to convert the fuzzy results into an output.

ANFIS integrates the philosophies of artificial neural networks (ANNs) and FIS and therefore, potentially presents all benefits of them in a unique framework. Through the hybrid learning, ANFIS is able to evaluate the relationships between inputs and target data by determining the optimum distribution of membership functions. Fig. 1 shows a basic ANFIS architecture. According to this figure, ANFIS architecture consists of two parts including premise and consequent parts. ANFIS has extensively used in various applications of science and engineering based on its ability to predict the non-linear relationships between input and output data [20–22].

To explain the modeling procedure by ANFIS, it is supposed that the FIS under consideration consists of two inputs (x, y) and one output (f) and the rule base includes two fuzzy rule set "if-then" as bellow [17]:

Rule I: if x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule II: if x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

in which p_i, q_i, and r_i are the consequent parameters to be settled. According to Jang [17] and Jang et al. [19], an ANFIS with five layers and two rules can be explained as follows:

Layer I: Every node i in layer I produces a membership grade of a linguistic label. For example, the node function of the ith node is:

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - v_i}{\sigma_1}\right)^2\right]^{b_i}} \tag{2}$$

in which Q_i^1 and x are the membership function and input to node i respectively. A_i is the linguistic label related to node i and σ_1, v_i, b_i are parameters that make changes in the form of the membership functions. The existing parameters in this layer are related to the premise part, as in Fig. 1(a).

Layer II: Each node in layer II computes the firing strength of each rule through multiplication:

$$Q_i^2 = w_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \quad i = 1, 2 \tag{3}$$

Layer III: The ratio of firing strength of the ith rule to the sum of firing strengths of all rule is obtained in this layer.

$$Q_i^3 = W_i = \frac{w_i}{\sum_{j=1}^{2} w_j} \quad i = 1, 2 \tag{4}$$

Layer IV: Every node i in this layer is a node function whereas Wi is the output of layer III. Parameters of this layer are related to consequent part.

$$Q_i^4 = W_i f_i = W_i(p_i x + q_i y + r_i) \tag{5}$$

Layer V: The incoming signals are summed in this layer and form the overall output.

$$Q_i^5 = \text{Overall Output} = \sum W_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{6}$$

3. Prediction of thermal conductivity of rocks through ANFIS

An ANFIS-based model was developed to predict TC of rocks. This model utilized four input parameters including uniaxial compressive strength, P-wave velocity, bulk density and porosity. These parameters are the most influential factors on TC of rocks. The input and output parameters utilized in this model and range of them are tabulated in Table 1. Fig. 2 shows the frequency distribution of utilized TC values in the proposed ANFIS-based model. The input datasets were randomly divided into two categories: 80% as the training datasets (35 datasets) for learning procedure and 20% as the testing