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Estimation of deformation modulus of coals using artificial neural networks (ANN)

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Abstract: In this study, the Young modulus (E) of different coals was investigated using artificial neural networks (ANN). For this purpose, a comprehensive literature survey was carried out to compile such datasets available for the ANN analyses. As a result of the literature survey, a database composed of 81 datasets was formed. In the ANN analyses, uniaxial compressive strength (UCS) and dry density (ρ_d) of coals were adopted as input parameters. The ANN analysis results demonstrated that the predictive model established in this study could be reliably used to estimate the E for different coals. The correlation of determination value (R^2) for the developed model is 0.85, which shows its relative success. In this context, this study can be declared a case study showing the applicability of ANN for the evaluation of E for a wide range of coal types. However, the number of samples and independent variables should be increased to obtain more comprehensive models in future studies.

Keywords: Coal; Deformation properties; Young modulus; Artificial neural networks

I. INTRODUCTION

The stability of coal measures strata in underground mines is of prime importance in sustainable and safe coal mining operations. The stability of coal measures strata has been investigated mainly using numerical modeling techniques [1–3]. In numerical modeling of rock masses, several rock strength properties such as uniaxial compressive strength (UCS), Young modulus (E), and Poisson's ratio (v) are required as input parameters. By adopting the above-mentioned rock properties, coal-bearing rock masses can be modeled using several methodologies such as the finite element method (FEM) and the discrete element method (DEM) [4–6]. Of the rock properties, the UCS and E are of prime importance to set forth the stability of coal pillars and the stress-strain relationship of coal-bearing strata. However, considering the heterogeneous structure of coals, the determination of E in the laboratory is tedious and requires special equipment such as high precision stiff loading machines, strain gauges, deformation jackets, or linear variable differential transformers (LVDTs). Hence, several theories have been postulated to estimate the E of different rock types in the literature [7−11]. Recently, soft computing algorithms such as adaptive neuro-fuzzy inference systems (ANFIS) and artificial neural networks (ANN) have gained popularity in dealing with most engineering geological problems because of their flexibility and high precision accuracy. [12–16].

However, apart from the studies by Pan et al. [17] and Lawal et al. [18], the implementation of regression and soft computing tools for the evaluation of E for different coals is quite limited. Therefore, there is a need to obtain comprehensive empirical models to evaluate the E of different coal types. For this purpose, a comprehensive literature survey was conducted to compile such datasets for soft computing analyses in this study. The most important theoretical and practical findings obtained from this literature survey are summarized as follows:

- The strength properties of coals increase in parallel with their rank [17].
- The variations in pulse wave velocity (V_p) are highly dependent upon the E of coals [19].
- The UCS of coals can be estimated from Schmidt Hammer tests [20−23].

However, the above findings are valid mainly for a small area of interest. Therefore, they have some limitations in dealing with larger datasets with different coal origins. Consequently, soft computing analyses with larger datasets are required to obtain more comprehensive relationships for the evaluation of coal strength and deformation properties.

In this study, the E of different coals was investigated using ANN analyses. On the basis of the collected data, a comprehensive empirical model is introduced. The details and mathematical expressions of the established model are also presented in this study to allow users to implement the proposed model more efficiently.

II. Database development

A comprehensive literature survey was conducted to compile quantitative data on the strength and deformation properties of different coal types. Unfortunately, a significant number of previous studies could not have been considered due to a lack of information on the physical and mechanical properties of coal, which are important as input parameters. As a result of the literature survey, a database composed of 81 datasets was collected including the dry density (ρ_d), UCS, and E (**Table 1**).

Table 1. *Datasets considered in this study*

ρ_d [g/cm^3]	UCS [MPa]	E [GPa]	n	Ref.
1.75–2.15	8.207–54.702	1.457–3.213	4	[19]
1.40–1.90	31.01–33.00	3.52–3.70	2	[24]
1.83–1.89	34.12–35.68	2.38–2.41	6	[25]
1.20–1.70	6.75–22.30	0.23–0.78	9	[26]
1.27–1.80	3.08–28.77	0.81–3.82	15	[27]
1.37–1.98	17.38–32.39	2.19–2.43	45	[28]

Using the database summarized in Table 1, several ANN analyses were performed to establish a comprehensive mathematical model for the evaluation of the E of different coals. Before performing the ANN analyses, the simple correlations of the considered variables were revealed by Pearson's correlation coefficient (r) and spearmen rho values, which are listed in **Table 2**. Accordingly, the ρ_d and UCS are moderately associated with the E of different coal types. Therefore, these two independent variables were selected as input parameters in ANN analyses.

Table 2. *Correlations of independent variables for the evaluation of E for different coal types*

Statistical indicator	ρ_d	UCS
Pearson's correlation coefficient, r	0.566	0.565
Spearman rho value	0.766	0.500

III. Artificial neural networks (ANN) analyses

ANN-based methods can analyze data, learn, save knowledge, and use it for future predictions [29, 30]. This parallel distribution learning algorithm applies to many problems, from social science to applied science. In most ANN models, a feedforward backpropagation algorithm is adopted. In this study, the neural network toolbox (nntool) was utilized to establish several neural networks in the MATLAB environment. Various possible network architectures with variable hidden layers and neurons were attempted to determine the most reliable ANN structure. For estimating the E for different coal types, the most convenient ANN architecture was found to be 2–6–1 (**Fig. 1**). The independent variables for the ANN analyses were selected as the UCS and ρ_d. To increase training efficiency during ANN analyses, the dataset was also normalized between –1 and 1, using equation (1).

$$V_n = 2 \cdot \frac{x_i - x_{min}}{x_{max} - x_{min}} - 1 \tag{1}$$

where x_i is the relevant parameter to be normalized, x_{min}, and x_{max} are the minimum and. maximum values in the dataset.

As a result of the ANN analyses, the E for different coal types can be estimated using equation (2). The subfunctions of equation (2) were determined based

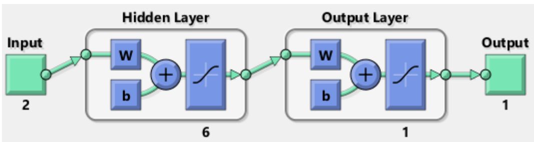

Figure 1. *ANN architecture adopted in this study*

on the deterministic approach previously described by Das [31] and they are listed in equations (3) to (10), where equations (9) to (10) are the normalization functions. According to the ANN analyses, the proposed model (equation (2)) correlates with a determination value (R^2) of 0.85, which shows its relative success.

$$E = 1.8233 \cdot tanh\left(\sum_{i=1}^{6} A_i + 1.1645\right) + 2.0264; \; R^2 = 0.85 \tag{2}$$

$$A_1 = 1.0654 \cdot tanh(7.5356^n \cdot UCS - 1.6385^n \cdot \rho_d - 1.6398) \tag{3}$$

$$A_2 = 0.85969 \cdot tanh(-14.0079^n \cdot UCS + 7.484^n \cdot \rho_d - 0.5834) \tag{4}$$

$$A_3 = -4.787 \cdot tanh(1.6683^n \cdot UCS - 4.2348^n \cdot \rho_d - 2.1176) \tag{5}$$

$$A_4 = 2.4436 \cdot tanh(0.56564^n \cdot UCS + 3.5425^n \cdot \rho_d - 0.43686) \quad (6)$$

$$A_5 = -7.7371 \cdot tanh(-1.2373^n \cdot UCS + 2.4793^n \cdot \rho_d - 0.93343) \quad (7)$$

$$A_6 = 0.25474 \cdot tanh(4.5541^n \cdot UCS - 4.5541^n \cdot \rho_d + 8.0908) \quad (8)$$

$$^nUCS = 0.0387 \cdot UCS - 1.1193 \quad (9)$$

$$^n\rho_d = 2.1075 \cdot \rho_d - 3.5311 \quad (10)$$

IV. Results and Discussion

Based on the ANN analyses, the proposed empirical model (Eq 2) was developed in this study. The performance of the proposed model was checked by correlating the predicted and measured E values for different coal types, which were previously reported by several researchers.

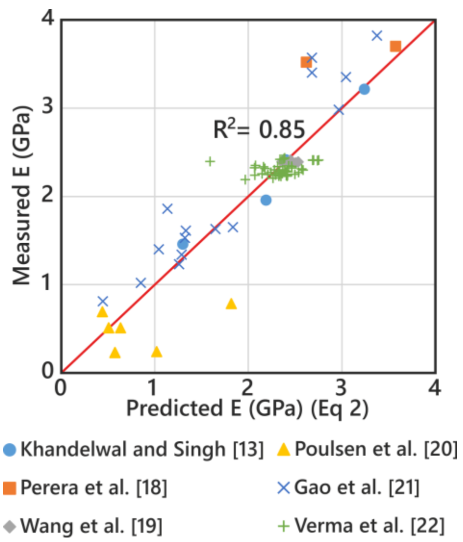

***Figure 2.** Predicted and measured E values for the proposed ANN model*

Consequently, the predicted and measured E values for different types of coal are in good agreement (**Fig. 2**). Therefore, the model established in this study can be reliably used to estimate the E of different coals.

The deformation properties of coals are well-known phenomena for coalbed methane recovery and CO_2 sequestration [32]. They are also important in estimating the bearing capacity of the coal masses [23]. Therefore, comprehensive models are needed for the evaluation of E for different coal types. In most engineering projects related to the underground coal mines, the UCS and ρ_d values have been measured routinely. Hence, the E of different coal types can also be estimated using these coal properties. In this context, this study can be declared a case study showing the applicability of ANN for the evaluation of E for a wide range of coal types. However, the number of samples and independent variables should be increased to obtain more comprehensive models in future studies. Anyhow, the present study can be declared a case study showing the applicability of ANN analyses for the evaluation of E for different coal types.

V. Results and Discussion

The E of coals is a fundamental parameter for determining the deformation behavior of the coal masses. However, because of the heterogeneity and complexity of the coal strata, the determination of E for different types of coal is challenging and requires special equipment in the laboratory. Therefore, it is necessary to obtain reliable and comprehensive models to estimate E for a wide range of rock types. With this study, a comprehensive predictive model is introduced to estimate the E of different coals. For this purpose, a comprehensive literature survey was carried out to compile datasets available for soft computing analyses. Consequently, a database composed of 81 datasets was formed (**Table 1**). Soft computing analyzes based on ANN were then performed to build a novel predictive model for the evaluation of E for different coals.

In the ANN analyses, the UCS and ρ_d values of coals were considered as input parameters. As a result of ANN analyzes, Eq. 2 was developed, which successfully estimated the E of the coals. For the sake of clarity, the sub equation systems behind equation (2) were also presented in this paper (equations (3) to (10)), to let users implement the proposed model efficiently. According to the performance of the proposed ANN model, it was determined that the predicted and measured E values are in good agreement (**Fig. 2**), indicating the relative success of the model. However, the number of samples and independent variables should be increased to obtain more comprehensive models in future studies.

Author Contributions

E. Köken: Conceptualization, Software, Writing, Review, Validation and Editing.

Disclosure Statement

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this document.

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