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Soft computing implementations for evaluating Los Angeles abrasion value of rock aggregates from Kütahya, Turkey

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Abstract: The Los Angeles abrasion value (LAAV) of rocks is a critical mechanical aggregate property for designing road infrastructures and concrete quality. However, the determination of this critical aggregate property is labour-intensive and time-consuming and thus, in the literature, there are many predictive models to estimate the LAAV for different rock types. However, most of them are based on classical regression analyses, limiting their broader usage. In this study, several soft computing analyses are performed to develop robust predictive models for the evaluation of LAAV of rocks in the Ilıca region (Kütahya – Turkey). The main motivation for implementing soft computing analyses is that precise predictive models might be useful when exploring suitable rock types that are manufactured in crushing–screening plants. For this purpose, a comprehensive laboratory schedule was established to obtain some inputs for the evaluation of LAAV. As a result of the soft computing analyses, four robust predictive models are developed based on artificial neural networks (ANN), multiple adaptive regression spline (MARS), adaptive neuro-fuzzy inference system (ANFIS) and gene expression programming (GEP) methodologies. The performance of the proposed models is investigated by some statistical indicators such as R^2 and RMSE values and scatter plots. As a result, the ANFIS-based predictive model turns out to be the best alternative to estimate the LAAV of the investigated rocks.

Keywords: Los Angeles abrasion value (LAAV), rock aggregate properties, predictive model, soft computing.

I. INTRODUCTION

The construction and building sector, which are driving forces in expanding economies, creates a substantial demand for goods and services, including many subsectors [1, 2]. One of the subsectors that plays a crucial role in geoengineering projects is the rock aggregate industry. The demand for construction aggregates, in this regard, can be evaluated based on three different groups regarding their origin (i.e., igneous, metamorphic, and sedimentary rocks). For example, rock aggregates with specific size fractions are obtained from igneous rocks such as andesite, basalt, syenite, gabbro and granite [3, 4]. Rock aggregates suitable for technical requirements are used in some infrastructures, such as water storage filtration and distribution systems and waste collection-treatment plants, and in some superstructures, such as buildings, bridges, railways, highways, etc [5−7].

To overcome stability issues in aggregate-related engineering structures, rock aggregates should withstand crushing, fragmentation, and deterioration when stacked, compressed, and subjected to surcharge loads. [8].

For this reason, the suitability of rock aggregates for use in the construction industry has been investigated through several testing methods such as aggregate impact value (AIV), aggregate crushing value (ACV), Los Angeles abrasion value (LAAV), Micro-Deval abrasion value (MDAV) [9–12].

Of the above-mentioned testing methods, LAAV and MDAL are well-accepted rock aggregate properties for evaluating rock aggregate suitability [7, 13–15]. However, these tests are hard to perform and necessitate unique graded samples. It was also reported that the LAAV test is labour-intensive and time-consuming. Therefore, numerous theories have been postulated to estimate the LAAV for different rock types [10, 14, 16–22]. However, most of these studies are based on classical regression analyses, limiting their broader use.

Nevertheless, it should be mentioned that artificial intelligence methods such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Neural Networks (ANN), Multivariate Adaptive Regression

Splines (MARS), Support Vector Machine (SVR), and Gene Expression Programming (GEP) are more sensitive to large datasets. Thus, they can provide better results compared to classical regression analyses [23, 24].

Based on the above comments, the present study aims to establish several predictive models to estimate the LAAV of rock aggregates in Ilıca region (Kütahya–Turkey). For this purpose, detailed laboratory studies are carried out to create a comprehensive database for soft computing analyses. Based on the ANFIS, ANN, MARS and GEP methodologies, four different predictive models are introduced in this study. The performance of these models is compared based on different statistical indicators.

The details and critical notes on how to implement these methodologies used to estimate the LAAV of the investigated rocks can be found in this research paper.

II. MATERIALS AND METHODS

The investigated rock types are exposed in the northeast part of Kütahya, Turkey (**Fig. 1**). These rock types are identified in the Miocene aged Tavşanlı volcanites, and they are mainly andesites, basalts, and basaltic andesites in lithology [25].

The investigated rocks have been considered as dimension stones and rock aggregate resources in the region. For laboratory studies, representative rock blocks are obtained from several locations around the Ilıca region.

During field observations, only unweathered rock blocks were obtained to mitigate the effects of weathering on rock engineering properties. While doing this, the qualitative approach suggested by the International Society of Rock Mechanics [26] was adopted to determine the weathering degree of rocks.

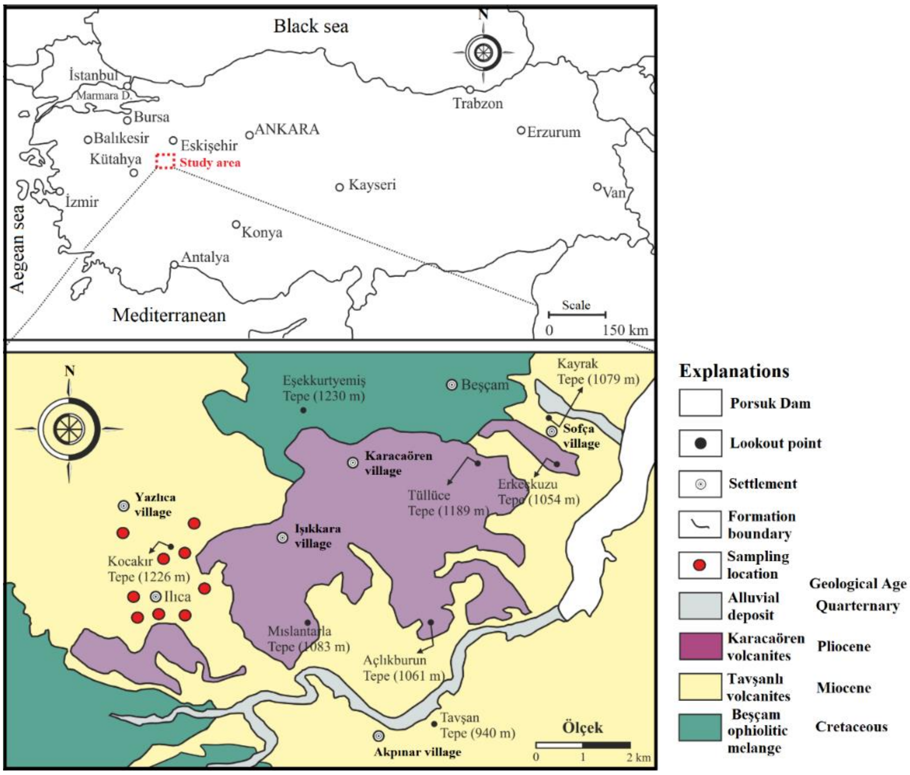

Figure 1. *Sampling locations and geological settings of the study area*

A total of 29 representative rock blocks were obtained for laboratory studies. For each rock block, physical and mechanical rock aggregate properties were determined. The laboratory studies were performed under oven-dried conditions. Each test was repeated at least three times, and average values were presented in this study.

III. LABORATORY STUDIES

The physical properties of rock aggregate consist of dry density (ρ_d) and water absorption by weight (w_a). These tests were performed by considering TS EN 1936 [27]. The mechanical rock aggregate properties considered in this study were AIV and LAAV.

These tests were also performed according to BS 812-112 [28] and TS EN 1097-2 [29], respectively. Laboratory test results are listed in **Table 1**. Accordingly, ρ_d, w_a, AIV and LAAV values were found to be between 2.59–2.74 g/cm^3, 1.19–3.80%, 12.01–24.43% and 12.27–25.46%, respectively.

Based on the database given in **Table 1**, soft computing analyses were performed.

Table 1. *Laboratory test results*

Lithology	ρ_d (g/cm[3])	w_a (%)	AIV (%)	LAAV (%)
Basalt	2.72	1.69	17.67	18.58
	2.67	1.91	16.40	21.14
	2.71	1.48	16.46	13.46
	2.72	1.71	13.10	15.25
	2.69	1.80	17.56	18.48
	2.67	2.46	17.10	23.72
	2.73	1.65	16.27	20.08
	2.69	2.70	23.96	25.46
	2.70	1.87	13.21	13.49
	2.71	1.60	15.74	16.78
	2.74	1.57	15.47	13.10
	2.73	1.45	15.02	17.97
	2.74	1.43	12.01	15.16
	2.74	1.59	14.28	12.27
	2.70	1.96	17.01	18.90
Basaltic andesite	2.71	2.15	12.33	15.46
	2.70	1.62	13.48	14.67
	2.71	1.96	20.77	23.45
	2.73	1.52	14.12	17.13
	2.67	2.53	17.51	20.31
	2.74	1.19	15.45	16.51
	2.69	2.28	14.11	17.12
	2.72	1.35	18.57	16.88
	2.68	2.05	21.31	23.90
Andesite	2.59	3.80	24.43	25.22
	2.61	1.93	18.58	18.76
	2.69	1.83	19.98	21.13
	2.62	1.90	21.25	20.39
	2.62	2.47	18.98	24.35

Explanations: ρ_d: dry density, w_a: water absorption by weight, AIV: aggregate impact value, LAAV: Los Angeles abrasion value

IV. Soft computing analyses

In this section, different soft computing methods, such as ANN, MARS, ANFIS, and GEP methodologies, were introduced.

For all methodologies, the input parameters are ρ_d, w_a and AIV with several combinations. Brief explanations of the adopted methodologies are given in the following subtitles.

1. Artificial neural networks (ANN)

Artificial Neural Networks (ANN) have gained popularity for their ability to predict dependent variables based on complex datasets.

Neural networks are commonly used in various engineering applications. In practice, they are trained through a feedforward backpropagation algorithm [30]. In this study, the neural network toolbox (nntool) was used to reveal a robust predictive model in the MATLAB environment. For this purpose, the dataset (**Table 1**) was randomly divided into training (70/100) and testing (30/100) datasets.

Various ANN architectures have been attempted to obtain the best predictive model. Before performing the analyses, the dataset was normalized between −1 and 1 to overcome overfitting problems. This normalization process is performed using Eq 1.

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

Where V_n is the normalized data, x_i is the data to be normalized, x_{min} is the minimum value in the dataset, and x_{max} is the maximum value in the dataset.

After the normalization process, the dataset was loaded into the MATLAB environment to perform the neural network analyses. The analyses remained until the minimum error was obtained. Herein, root means square error (RMSE) was adopted as an error metric. Based on the analysis results, the most feasible ANN model was formulated by using the weights and biases extracted from the ANN outputs.

2. Multiple Adaptive Regression Spline (MARS)

MARS was first proposed by Friedman [31] as a nonparametric regression model. There are two important components in typical MARS models. The first one is the forward pass, and the other one is the backward pass. In the forward pass, the analyses are initiated with constant terms called basis functions (BFs). In the second part, BFs are connected to each other by employing linear regression models. It is a simple but powerful methodology to deal with datasets with a number of independent variables. MARS analyses were performed using software R, and details on the MARS-based predictive model are introduced in the following section.

3. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is a hybrid approach that combines the fuzzy logic inference system (FIS) and ANN to establish a more efficient and accurate system.

In most ANFIS models, the Sugeno fuzzy reasoning algorithm is adopted based on numerous membership functions [32, 33]. Similar to the ANN analyses, ANFIS models were run using MATLAB R2021b. Input parameters are represented by several Gaussian membership functions. Based on several if-then rules, a novel ANFIS-based predictive model is proposed in this study.

4. Gene expression programming (GEP)

GEP is another soft computing algorithm that uses evolutionary techniques to develop a mathematical formula which represents the relationship between the dependent and independent variables.

The GEP was developed by Ferreira [34] and has gained popularity in most geoengineering publications [35–37]. The GEP analyses were performed using GeneXproTools. Several numbers of chromosomes, head sizes and gene sizes were attempted to obtain the most feasible GEP model.

V. Results and Discussion

1. ANN analysis results

Based on several ANN analyses, the best ANN architecture was found to be 3–4–1. It means that there were three inputs (ρ_d, w_a and AIV), four hidden layers and one output (LAAV) (**Fig. 2**).

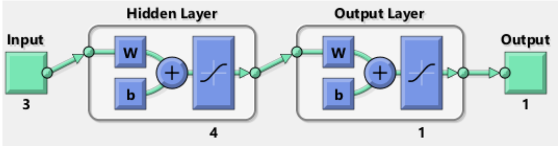

Figure 2. *ANN architecture adopted in this study.*

The mathematical formulations of the proposed ANN model were revealed by considering the deterministic approach provided by Das [38], which is given by Eq 2.

$$Y = f_{sig}\left\{ b_0 + \sum_{j=1}^{n}\left[w_j \times f_{sig}\left(b_{hj} + \sum_{i=1}^{m} w_{ij} \times \delta_i \right)\right]\right\} \quad (2)$$

where Y is the output variable (LAAV), b_0 is the bias in the output layer, n is the number of neurons in the hidden layer (n=4 in this study), j denotes a specific neuron in the hidden layer, w_j is the weight of the connection between the jth hidden layer and the single output neuron, b_{hj} is the bias in the jth neuron of the hidden layer, w_{ij} is the weight of the connection between the ith input parameter and the jth hidden layer, δ_i is the normalized input parameter, f_{sig} is the nonlinear transfer function (tanh).

Based on the above deterministic approach, the LAAV can be estimated by the equations (Eqs 3 – 10). To estimate the LAAV of the investigated rocks, these equations can be easily implemented by coding them into any computational language.

$$LAAV = 6.595\tanh\left(\sum_{i=1}^{4} A_i - 0.2747\right) + 18.865 \quad (3)$$

$$A_1 = 1.2173\tanh\left(2.8187\,{}^{n}\rho_d + 0.85004\,{}^{n}w_a + 3.6887\,{}^{n}AIV - 0.5154\right) \quad (4)$$

$$A_2 = -1.2866\tanh\left(-0.15365\,{}^{n}\rho_d - 2.9709\,{}^{n}w_a - 0.06788\,{}^{n}AIV - 1.1679\right) \quad (5)$$

$$A_3 = 2.1584\tanh\left(-1.891\,{}^{n}\rho_d - 1.507\,{}^{n}w_a - 2.1233\,{}^{n}AIV - 0.90154\right) \quad (6)$$

$$A_4 = 1.9491\tanh\left(3.5233\,{}^{n}\rho_d + 0.42358\,{}^{n}w_a + 5.3114\,{}^{n}AIV + 2.5011\right) \quad (7)$$

Normalization functions:

$${}^{n}\rho_d = 13.333\rho_d - 35.533 \quad (8)$$

$${}^{n}w_a = 0.7663w_a - 1.9119 \quad (9)$$

$${}^{n}AIV = 0.161AIV - 2.934 \quad (10)$$

2. MARS analyses results

Based on four BFs, the LAAV can also be investigated considering the MARS methodology. Accordingly, the LAAV can also be estimated by the following equations. The BFs listed in Eqs 12 – 15 are based on the global maxima (max function) in terms of different input parameters.

$$LAAV = 15.19 + 0.89BF1 - 121.55BF6 - 133.58BF9 \quad (11)$$

$$BF1 = \max\left(0; AIV - 12.01\right) \quad (12)$$

$$BF6 = \max\left(0; \rho_d - 2.73\right) \times BF1 \quad (13)$$

$$BF7 = \max\left(0; 2.73 - \rho_d\right) \times BF1 \quad (14)$$

$$BF9 = \max\left(0; 1.87 - w_a\right) \times BF7 \quad (15)$$

3. ANFIS analyses results

In the context of the ANFIS analyses, three input parameters were considered (**Fig. 3a**). During the training process, RMSE was adopted as an error metric.

The ANFIS analyses were performed until the minimum RMSE values were obtained (**Fig. 3b**). According to the ANFIS model structure (**Fig. 3c**), each input parameter was represented by five novel Gaussian membership functions. Consequently, five if-then rules activated the ANFIS model (**Fig. 3d**).

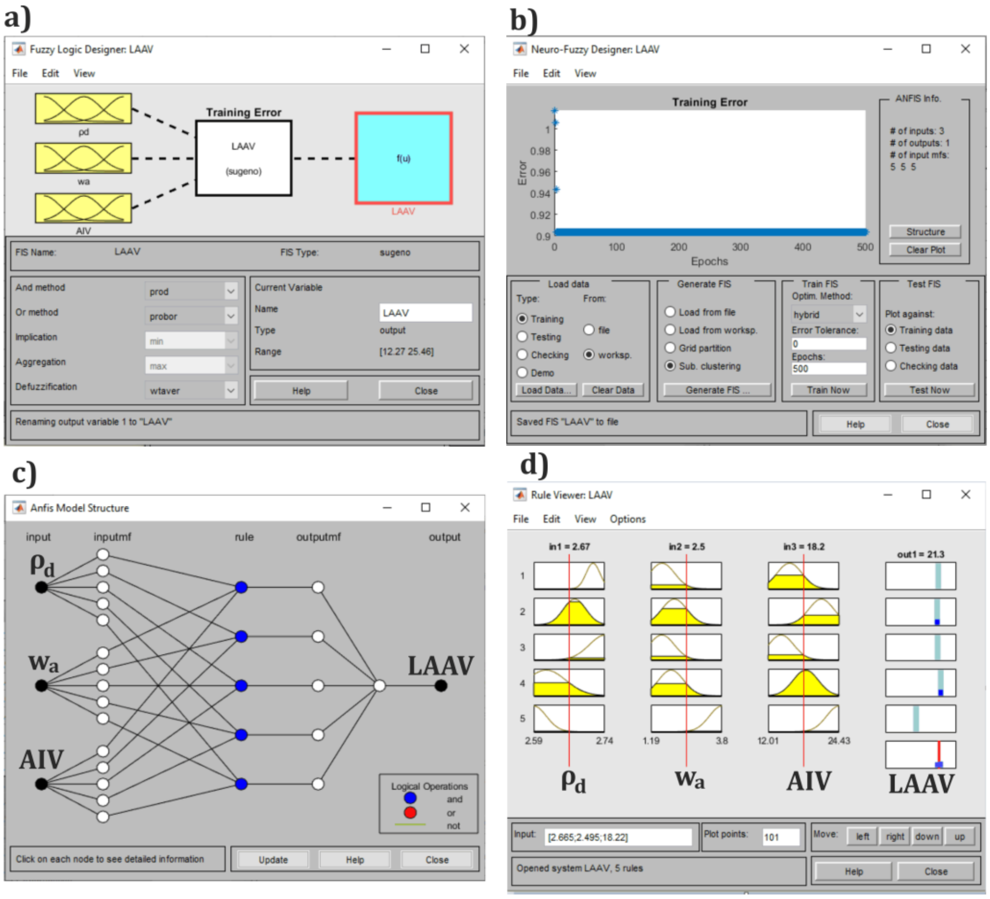

***Figure 3.** ANFIS outputs a) Input parameters b) Training process c) ANFIS model structure d) Rule viewer*

4. GEP analyses results

Based on GEP analyses, the last predictive model was proposed. The sub-expression trees (Sub-ETs) are given in **Fig. 4**. The mathematical expressions of these Sub-ETs are also listed in Eqs 16 – 19.

$$LAAV = 0.9872\sum_{i=1}^{3} A_i + 0.1719 \tag{16}$$

$$A_1 = \max\left(\left(\min\left(2.46, w_a\right)\right)^2, 2.53\right) \tag{17}$$

$$A_2 = \frac{\dfrac{\dfrac{w_a + AIV}{2} + AIV}{2} + \min\left(w_a, 2.47\right)}{2} \tag{18}$$

$$A_3 = \frac{\left(w_a^{\,2} \times -0.499\right) + \left(-0.133 + AIV\right)}{2} \tag{19}$$

By implementing the above equations, LAAV values can be easily estimated. The performance of the proposed predictive models is also investigated based on several statistical indicators, which are given in the following section.

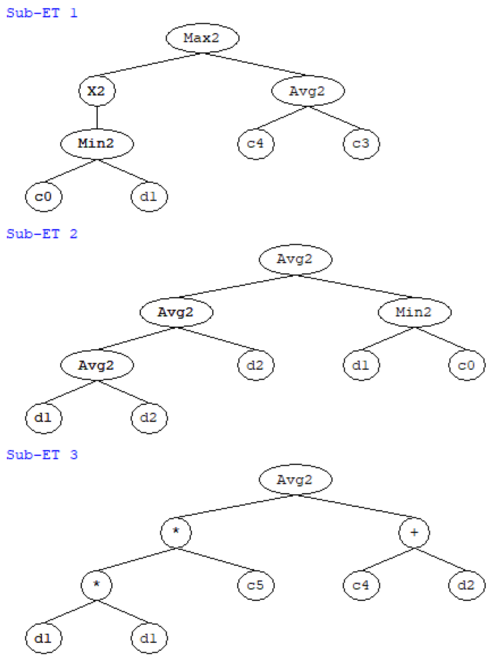

Figure 4. *Sub-ETs of the proposed GEP model (d_0: ρ_d, d1: w_a, d_2: AIV, g_1c_0: 2.469, g_1c_3: 2.527, g_1c4: 2.528, g_2c_0: 2.469, g_3c_4: −0.133, g_3c_5: −0.499).*

5. Performance Evaluation

The performance of the proposed predictive models is investigated based on several statistical indicators, such as correlation of determination (R^2) and RMSE values. The statistical indicators are calculated by the following equations:

$$R^2 = \frac{n\sum xy - \sum x \sum y}{\sqrt{n\sum x^2 - \left(\sum x\right)^2}\sqrt{n\sum y^2 - \left(\sum y\right)^2}} \tag{20}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - x_i\right)^2}{n}} \tag{21}$$

Where x is the predicted variable, y is the measured variable, and n is the number of datasets.

Focusing on the training (70/100) and testing (30/100) datasets, the R^2 and RMSE values are listed in **Table 2.**

Table 2. *Performance indicators of the proposed predictive models*

Methodology	Training dataset		Testing dataset	
	R^2	RMSE (%)	R^2	RMSE (%)
ANN	0.81	1.624	0.98	0.296
MARS	0.86	1.523	0.72	2.096
ANFIS	0.92	1.042	0.98	0.468
GEP	0.72	1.965	0.86	1.295

Accordingly, for training and testing datasets, the R^2 and RMSE values were found to be between 0.72–0.98 and 0.296–2.096%, respectively (**Table 2**). Based on the calculated performance indices, the ANFIS-based predictive model provides the best prediction performance when considering the whole dataset. On the other hand, the ANN-based predictive model, with its explicit mathematical formulations, can also be regarded as a concise model to estimate the LAAV of the investigated rocks. The scatter plots of the models are also given in **Fig. 5**. In **Fig. 5**, the performance of the predictive models is illustrated by focusing on the whole dataset (n=29).

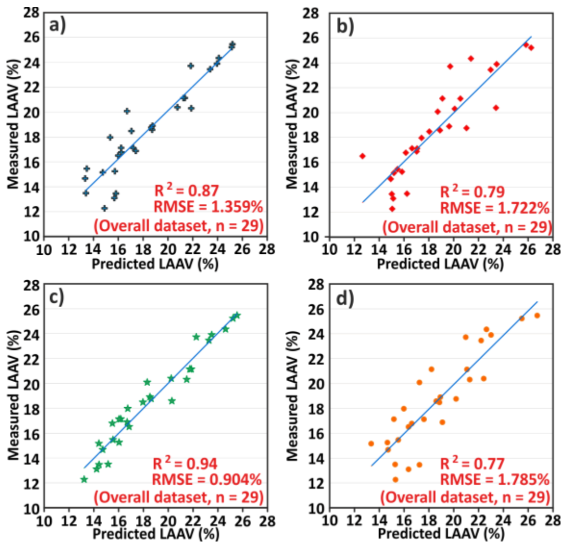

Figure 5. *Scatter plots of the proposed predictive models a) ANN b) MARS c) ANFIS d) GEP*

Similar to what has been stated earlier, the scatter plots also suggest that the ANFIS-based predictive model provides concise LAAV values and, thus, this methodology can be regarded as a robust methodology for the evaluation of LAAV. However, this methodology can have some difficulties in that it is a black-box model, and there are no definite mathematical expressions as an output in the ANFIS analyses. It should be herein mentioned that the outputs were extracted from the ANFIS model based on some computational commands (e.g., evalfis) in the MATLAB environment.

When explicit mathematical formulations are desired to estimate the LAAV of rocks, the ANN-based predictive model (Eqs. 3–10) can also be a coherent choice.

On the other hand, the GEP and MARS models should be improved by enhancing the number of datasets. These models often provide more accurate results by considering larger datasets.

6. Conclusions

In this study, robust predictive models are introduced to estimate the LAAV of the rocks in the Ilıca region (Kütahya–Turkey). For this purpose, a comprehensive laboratory schedule was established to obtain some inputs for the evaluation of LAAV. Consequently, a database composed of 29 datasets was generated (**Table 1**). As a result of the soft computing analyses, four robust predictive models are developed. The performance of the proposed models is investigated by some statistical indicators such as R^2 and RMSE values and scatter plots. As a result, the ANFIS-based predictive model turns out to be the best alternative to estimate the LAAV of the investigated rocks. Nevertheless, in this study, some explicit mathematical formulations are also provided based on the ANN methodology. This model can also be considered and coded into any computation language for its possible implementations. Last but not least, the MARS and GEP models should be improved by enhancing the database and adding some input parameters such as mineralogical features and/or quantitative knowledge on rock weathering.

It is highly recommended to investigate the weathering degree of the rocks exposed in the Ilıca region. In this way, the physical and mechanical aggregate properties and their possible variations can be thoroughly revealed. The findings obtained from the present study and recommendations stated are believed to be beneficial for the evaluation of LAAV for the investigated rock types.

AUTHOR CONTRIBUTIONS

E. Köken: Conceptualization, Experiments, Analyses, Writing, Review 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 paper.

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