Applied Computing and Geosciences 16 (2022) 100101

Contents lists available at ScienceDirect

Applied Computing and Geosciences

journal homepage: www.sciencedirect.com/journal/applied-computing-and-geosciences

A combined application of two soft computing algorithms for weathering degree quantification of andesitic rocks

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A R T I C L E I N F O

Keywords:
Andesitic rocks
Artificial neural network
Explicit neural network formulation
Fuzzy inference system
Weathering degree

A B S T R A C T

Understanding the variations in physical and mechanical behavior of rock materials due to progressive weathering is vital to carry on time and cost-effective engineering projects. Up to date, soft computing algorithms have been established to quantify the weathering degree (WD) of various rocks due to better prediction performance and problem-solving capability. However, the complexity of the weathering process does not allow the use of a single weathering quantification model for a wide range of rock types. Therefore, this study aims to provide a practical, quantitative, and effective framework for predicting the WD of andesitic rocks. To fulfill the aims of this study, a wide range of cases were collected from the previous studies to establish a predictive model based on dry unit weight (γ_d), effective porosity (n_e), and uniaxial compressive strength (UCS). Consequently, a combined application of fuzzy inference system (FIS) and artificial neural network (ANN) was introduced to assess the WD of the investigated andesitic rocks. The WD ratings were presented as four different weathering classes (from fresh (W_0) to highly weathered (W_3)). Since most soft computing algorithms are black-box models that cannot be efficiently utilized in any other study, an explicit neural network formulation was firstly developed for WD prediction in this study. As a result, the proposed formulation will provide a practical and straightforward assessment of WD for andesitic rocks. However, to improve the reliability and consistency of the proposed model, different datasets should be used in the explicit neural network formulation proposed.

1. Introduction

Weathering is a crucial parameter principally for rock masses affected by the exposure to water and dynamic loading during the operational life of the engineering project (Mehrotra et al., 1991; Mitra, 1991; Goel et al., 2013). The qualitative weathering assessment recommended by the International Society of Rock Mechanics (ISRM) (2007) is widely preferred for a time-effective and straightforward approximation. However, in the design stages of engineering projects, quantitative weathering degree determination is required in assessing geotechnical zonation in dam sites and studying the feasibility of rock masses (Chala and Rao, 2021; Karaguzel and Kilic, 2000). Weathering is one of the parameters for evaluating the excavability and rippability of the rock, which is also directly related to the selection of the type of excavation that influences the excavation costs (Scoble and Muftuoglu, 1984; Singh et al., 1987; Pasamehmetoglu et al., 1988; Karpuz, 1990; Ceylanoglu et al. 2007). The selection of the excavation type also strongly influences the project time and hence the budget of the project.

A considerable amount of literature has been documented for the quantitative assessment of WD for various types of rock. Most of these studies involve predictive regression models as well as proposed weathering indices based on some mineralogical, petrographical, chemical, physical, and mechanical properties of different rock materials. Less amount of studies focused on the WD of andesitic rock samples using simple or multiple regression models (Saito, 1981; Koca, 1995; Karpuz and Pasamehmetoglu, 1997; Arıkan et al., 2007; Koca and Kıncal, 2016). More recently, Yavuz (2011) and Çelik and Aygün (2019) studied the variations in the physical and mechanical properties of andesitic rocks due to accelerated aging tests in their laboratory studies.

The effect of weathering is mostly pronounced in grain-matrix contacts in andesitic rocks; the microcrack growth and formation of clay minerals are promoted along these boundaries (Kadakci Koca and Koca, 2019). On the other hand, the changes in the microstructural properties are not always significantly correlated with the variations in physical and mechanical properties (Takarli and Prince-Agbodjan, 2007; Kassab and Weller, 2015). Hence, discriminating the signature of the increasing

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https://doi.org/10.1016/j.acags.2022.100101
Received 24 June 2022; Received in revised form 17 September 2022; Accepted 1 October 2022
Available online 4 October 2022
2590-1974/

weathering on the physical and mechanical properties becomes challenging principally between fresh, slightly, and moderately weathered rocks. In this case, rocks having similar physical and mechanical properties may have different weathering grades that result in distinct deformation behavior under water-saturated and dynamic loading conditions. This phenomenon has been explained by overlapping of physical and mechanical rock properties in the transition between two weathering grades (Irfan, 1996; Aydın and Basu, 2006; Arıkan et al., 2007; Gökçeoğlu et al., 2009; Dağdelenler et al., 2011). In recent years, various research techniques such as artificial neural network (ANN), fuzzy inference system (FIS), and adaptive fuzzy inference system (ANFIS) have been applied to the determination of WD for various rock types as these techniques are better in dealing with uncertainty and complexity in the dataset (Zorlu, 2008; Gökçeoğlu et al., 2009; Dağdelenler et al., 2011; Hatır, 2020). Nevertheless, the WD of andesitic rocks has not been investigated using soft computing methods, although andesites are the second most common volcanic rock after basalts in terms of their abundance and distribution in outcrops (Read and Watson, 1973; Bell and Wright, 1985). Therefore, proper identification and interpretation of the WD of andesitic rocks would enable one to use andesites in broader engineering fields.

Studies concentrated on estimating the WD of different rock types using soft computing techniques have found no significant differences between the performance of the models constructed by ANN, FIS, and ANFIS. However, they can predict the WD more accurately than the regression models. For example, Zorlu (2008) constructed a FIS model to quantify the three weathering degrees (W_1–W_3) of building stones under conservation as a function of the Schmidt hammer value (SHV) and the fractal geometry. As a result of the study, she found prediction error percentages up to 17.5% for 114 rock blocks. On the other hand, Gökçeoğlu et al. (2009) compared the performance of models constructed by ANN and FIS. They used 32 specimens involving the (n_e), P-wave velocity (V_p), and uniaxial compressive strength (UCS) to predict five WD of granites from Harsit granitoid in NE Turkey. They concluded that the ANN model exhibited better learning capacity and the FIS has better generalizability. Similarly, Dağdelenler et al. (2011) compared the performance of models constructed by ANN, ANFIS, and non-linear multiple regression analyses. They used 84 specimens involving the dry unit weight (γ_d), $n_{e,}$ and UCS to predict five weathering degrees of Koprukoy granites in central Anatolia, Turkey. They pointed out that the overall performances of the three models are close to each other. Finally, Hatır (2020) investigated the weathering classification of historic buildings composed of dacite presenting five weathering degrees. A novel AHP-based visual weathering classification and P-wave velocity classification were embedded into the FIS model in that study. However, the performances of the proposed models was not quantified in the mentioned study.

Despite the high-level performances of soft computing models aiming at WD prediction in the above-mentioned studies, the main limitation is that each WD was assigned to a fixed and exact value (e.g., W_0: 1, W_1: 2, W_2: 3, etc.). The present study also differs from the other studies in that it assigns weathering degree ratings (WDRs) as intervals (ranging from 0 to 1) to four different weathering degrees (W_0 to W_3). Therefore, the WDRs ranging from 0 to 1 were achieved initially from a novel FIS model. Because FIS does not require the measured (observed) output to be represented directly in the model, unlike ANFIS or ANN, it instead gives a new insight into the output based on some sets of rules and the membership functions defined by the expert. Subsequently, WDRs were subdivided into four intervals representing four WD classes to eliminate the overlapping phenomenon. The WDRs were then introduced into the ANN model. The main limitation of ANN and ANFIS is that they are black-box models in which the fundamental hidden formula is not the point of interest (Khorchani and Blanpain, 2005; Guven et al. 2006; Aytek et al. 2008; Gkountakou and Papadopoulos, 2020). In this case, most of the models based on ANN cannot be used in any other studies. To overcome this case for WD prediction, the explicit neural network formulations derived from the ANN model were first presented in this study. One can use the proposed methodology on the samples collected from the planned derivation tunnel, cofferdam, or spillway areas where routine drilling works and laboratory measurements have already been done and can make a thematic map showing the distribution of the weathering grade towards depth and on the surface. Accordingly, the enhanced permeability and the need for grouting can be evaluated. The model can also be used to determine the weathering degree as an input in excavability and rippability classifications for highway or tunnel route projects. These examples can be extended depending on the needs of the engineering projects.

2. Materials and methods

2.1. Database development

Gupta and Rao (2001) stated that the chemical weathering indices could not be applied to all rocks due to different chemical processes associated with the rock type, tectonic, and climatic conditions of the environment. Hence, physical, mechanical, and index properties of rock materials to predict WD have been widely used for various rock types (Irfan and Dearman, 1978; Hack and Price, 1997; Tuğrul and Gürpınar 1997; Kılıç, 1999; Gupta and Rao, 2001; Tuğrul, 2004; Gürocak and Kılıç, 2005; Ceryan et al., 2008; Basu et al., 2009; Heidari et al., 2013; Dağ et al., 2013; Momeni et al. 2015; Udagedara et al., 2017; Gomes Marques et al., 2021; Zhang et al., 2021). On the other hand, only Irfan (1996) and Aydın and Basu (2006) have dealt with the overlapping problem of physical and mechanical rock properties due to progressive rock weathering. They have searched for a single weathering index to overcome the overlapping problems. Nevertheless, the overlapping along with the weathering degree zones was observed inherently (Gökçeoğlu et al., 2009; Dağdelenler et al., 2011). For this reason, using a single parameter to predict WD can yield misleading results. Fundamental physical and index properties such as γ_d, water absorption by weight (w_a), n_e, and V_p can be highly correlative parameters to evaluate rock weathering.

However, Tandon and Gupta (2015) revealed that the V_p is a very sensitive to changes in rock composition and texture. It shows substantial changes even in samples with similar mineral composition and texture. Similar results were also found by Kadakci Koca and Koca (2021). In addition, the sole use of uniaxial compressive strength (UCS) is not recommended in weathering degree determination (Gupta and Rao, 2001; Basu et al., 2009; Ündül and Tuğrul, 2012). Kadakci Koca and Koca (2019) indicated that the use of n_e and UCS together reflects variations in mineral content and therefore could be used to estimate WD. The parametric studies presented for the determination of the WD of different rock types highlighted the importance of the parameters selected in the predictive models. On the other hand, if there is a strong correlation between the independent variables (predictors), multicollinearity occurs in the dataset, which can severely violate the results of regression models. However, it was revealed that ANN could principally deal with multicollinearity and achieve better prediction performance than the multiple regression models (De Veaux and Ungar, 1994; Garg and Tai, 2013; Obite et al., 2020). From this point of view, multiple parameters that are routinely measured in geomechanical surveys were selected to predict WD in the present study. The dataset including γ_d, $n_{e,}$ and UCS of various andesitic rocks, was provided from the extensive literature survey (Table 1). However, a wide range of samples in the literature could not be incorporated into the database due to the lack of information on the WD or chemical/textural identification of those samples. In this direction, the andesitic rock samples were selected, whose weathering grades were clarified based on thin-section or in-situ qualitative observation or particular weathering indices. As a result, the database (Table 1) consists of 182 samples with different weathering grades (Fig. 1).

Variations in the size of the dataset involving different WD literally

Table 1
Different cases used in this study.

Code	Reference	Rock Type	Number of the samples (N)	Location	Weathering grade	Method of determination
S1	Alkan (2017)	Andesite	34	Gümüşhane-Turkey	W_0 to W_1	Thin section observation
S2	Czinder and Török (2020)	Andesite	8	Hungary	W_0 to W_2	Thin section observation
S3	Dağ (2019)	Andesite[a] Trachyandesite[a]	27	Menemen, Aliağa-İzmir-Turkey	W_0 to W_3	Classification proposed by Koca and Kıncal (2016)
S4	Demirci (2013)	Andesite[a]	28	İzmir-Bornova-Turkey	W_1 to W_3	In-situ qualitative
S5	Duman (2013)	Andesite[a]	15	İzmir-Karşıyaka-Turkey	W_1 to W_2	In-situ qualitative
S6	Kadakci Koca and Koca (2019)	Andesite[a]	17	İzmir, Balçova- Turkey	W_1 to W3	Classification proposed by Koca and Kıncal (2016)
S7	Köken (2019)	Basaltic andesite	10	Kütahya-Turkey	W_0	Thin section observation In-situ qualitative
S8	Köken and Özarslan (2018)	Andesite	19	Havran, Balıkesir-Turkey	W_0 to W_3	Classification proposed in the same work[b]
S9	Kurtuluş et al. (2010)	Andesite	12	Cape Kaskaval, Imbros Island-Turkey	W_0	In-situ qualitative
S10	Özden (2006)	Andesite	10	Zonguldak-Turkey	W_2 to W_3	In-situ qualitative
S11	Tembo (2020)	Andesite[a] Trachyandesite[a]	2	İzmir-Bornova-Turkey	W_0 to W_1	In-situ qualitative

[a] Classification based on the total alkali-silica diagram of Le Bas et al. (1986).
[b] a new classification based on ne (%), UCS (MPa), loss on ignition (%) and Schmidt hammer rebound value.

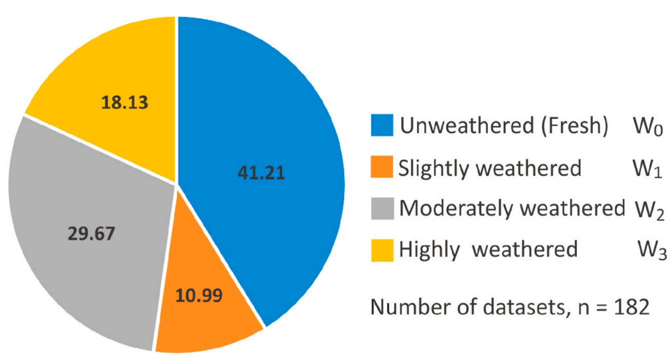

Fig. 1. Distribution of the andesitic rock samples with respect to different weathering grades in the database.

compare well with the outcrops showing such an unequal distribution of WD. Therefore, the adopted database in this study exhibits uncertainty and complexity in the distribution of WD as in the real case.

The reviewed literature also involves thin section observations and X-Ray diffraction and modal analysis results. The main phenocrysts of the reviewed andesites are mainly plagioclase, feldspar, pyroxene, and hornblende, with minor phenocrysts of biotite and olivine. Accessory minerals include magnetite. Basaltic andesite type has a higher proportion of olivine phenocrysts and less alkali feldspar than the andesites and trachyandesites. Andesites in the database present hypocrystalline, porphyritic, hyalopilitic, and pilotaxitic textures. The matrix of the rocks is formed by volcanic glass and microliths.

The microliths are mainly plagioclase, quartz, biotite, hornblende, and opaque minerals. The percentage of the matrix (40%–60%) increases, and the rate of phenocrysts decreases with progressive rock weathering. Epidote, chlorite, and clay minerals, sericitization of plagioclase minerals are clear indicators of rock weathering and alteration. As WD increases, the γ_d and UCS decrease, while n_e increases exponentially (Fig. 2).

Fig. 2 indicated that the variations in the n_e and UCS values are more distinct between different weathering grades than the γ_d. The relationship between n_e and γ_d is a generalized linear model with log-link. Both parameters (γ_d, UCS, and n_e) significantly overlap along with the WD

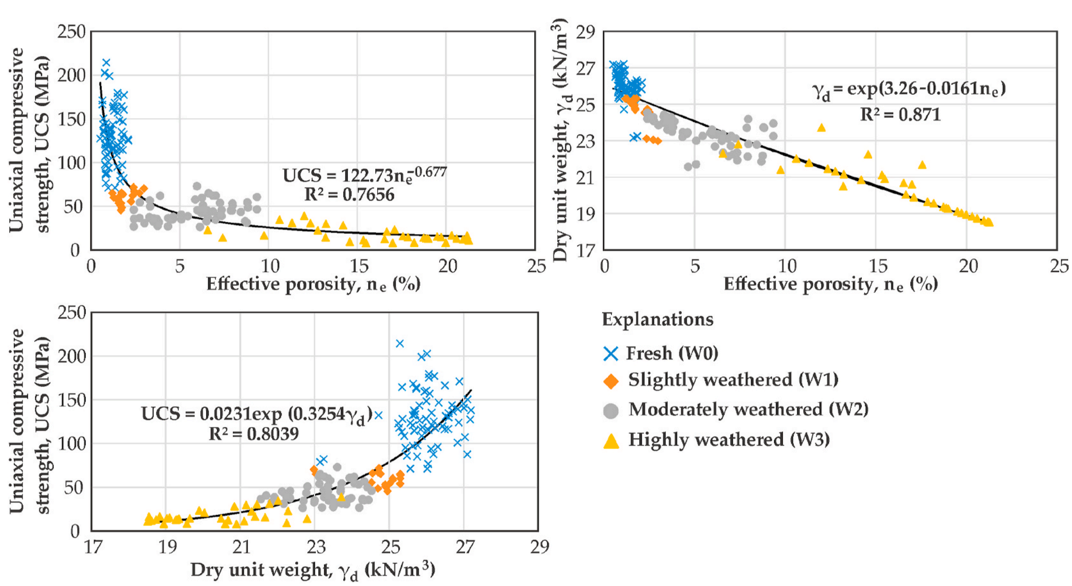

Fig. 2. Variations in selected rock properties with regard to rock weathering.

borders (Fig. 2). After the stage of W_1, an increase in n_e is more pronounced, and therefore a significant decrease in UCS is observed. The statistics of the 182 cases are summarized in Table 2. Accordingly, the mean γ_d, n_e, and UCS values ranged between 20.38 and 25.99 kN/m^3, 1.22–16.10%, and 17.47–129.27 MPa, respectively. When considering the mean UCS values, the investigated andesitic rocks were identified from very low to high strength rocks, according to Deere and Miller (1966). On the other hand, γ_d and n_e values can be classified as low to moderate and low to high, respectively, according to Anon (1979).

2.2. Quantifying the weathering degree by FIS

The fuzzy sets were first presented by Zadeh (1965) as a mathematical technique to represent both qualitative and quantitative interpretations. The advantage of fuzzy inference system (FIS) is that the experiences of users could be integrated into such FIS analyses, which enables analyzing their problems in more detail.

Fuzzy models can be constructed based on three different algorithms: Mamdani, Takagi-Sugeno, and Tsukamoto. Osna et al. (2014) stated that the overall process of both methods is similar, but only the final rule structures differ. Alvarez Grima (2000) and Gökçeoğlu et al. (2009) stated that the Mamdani's FIS algorithm (Mamdani and Assilian, 1999) is one of the most well-organized techniques to solve complex problems (Fig. 3).

Contrary to the crisp sets (0,1), in fuzzy set theories, dependent and independent variables are represented by membership functions that vary from 0 to 1. Common membership functions used in most FIS applications namely the Gaussian, triangular and trapezoidal ones (Cheng et al. 2019).

Mishra and Basu (2013) demonstrated that the shape of membership functions is enormously influential on fuzzy inference. Dombi (1990) also mentioned that the system output is highly influenced by the membership functions and sensitive to the properties of the membership function. Membership functions and fuzzy rules are developed by expert knowledge considering the expected relevancy between independent and dependent variables. The number of rules depends on the expert's

Table 2
Descriptive statistics of the cases considered in this study.

γ_d (kN/m^3)	W_0	W_1	W_2	W_3
Min	23.15	22.98	21.56	18.52
Mean	25.99	24.67	23.31	20.38
Max	27.20	25.31	24.53	23.72
Std. dev	0.71	0.74	0.77	1.41
Q_1	25.67	24.59	22.80	19.07
Q_2	26.00	24.90	23.36	20.49
Q_3	26.49	25.10	23.92	21.43
N	75	20	54	33
n_e (%)	W_0	W_1	W_2	W_3
Min	0.52	1.20	2.41	6.57
Mean	1.22	1.91	5.73	16.10
Max	2.12	2.99	9.35	21.28
Std. dev	0.40	0.50	2.05	4.10
Q_1	0.84	1.56	3.75	12.99
Q_2	1.15	1.71	6.07	17.00
Q_3	1.51	2.39	7.29	19.61
N	75	20	54	33
UCS (MPa)	W_0	W_1	W_2	W_3
Min	71.21	45.47	26.47	8.00
Mean	129.27	59.69	43.53	17.47
Max	214.36	71.80	73.00	39.03
Std. dev	30.84	7.28	11.19	8.23
Q_1	113.21	53.65	35.15	11.86
Q_2	127.48	60.10	41.45	14.44
Q_3	146.65	65.26	51.76	22.69
N	75	20	54	33

Min: minimum, Max: maximum, Std. dev: standard deviation; Q_1: lower (first) quartile; Q_2: median (second quartile); Q_3:upper (third) quartile; N: number of cases.

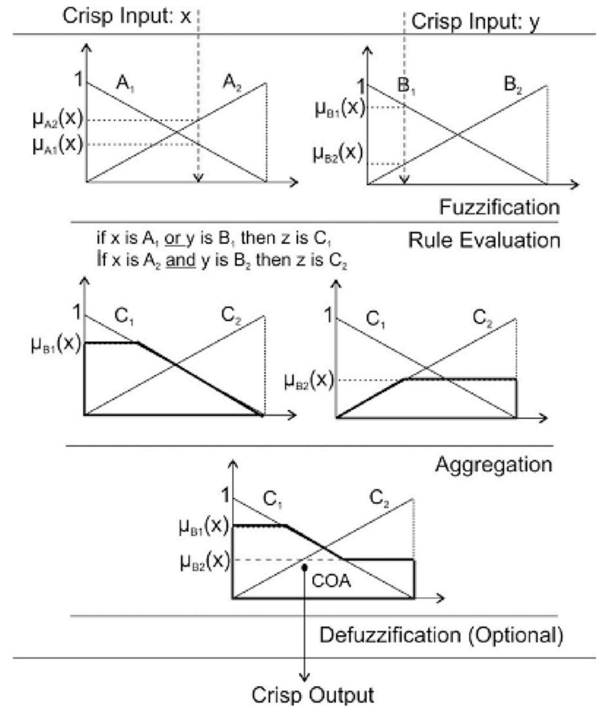

Fig. 3. Generalized structure of the Mamdani's fuzzy inference system (Osna et al., 2014).

opinion based on the possible combinations of input variables with the output. The final fuzzy output is obtained through aggregation of all local results. Defuzzification fundamentally expresses converting a fuzzy set into numerical values that can be used in a great number of engineering applications. Among the variety of defuzzification methods, the centroid method is commonly used due to its simplicity (Zorlu, 2008; Gökçeoğlu et al., 2009). In this study, Mamdani's FIS algorithm with centroid defuzzification method was adopted. Triangular and trapezoidal membership functions that are illustrated in Fig. 4 were constructed. Based on a detailed investigation of the cases, out of 64 combinations of predictive variables, 42 different if-then rules were constructed regarding various weathering degrees (Table 3).

Once the FIS output provided WDR values for each case in a range between 0 and 1, these WDR ratings were considered as the quantitative description of WD. After that, the WDRs representing the four weathering degree classes were imported into the ANN model.

2.3. Combining ANN with FIS

The artificial neural network (ANN) has been widely assumed to be a robust technique when focusing on complex datasets. Until recently, FIS and ANN were used separately and compared with each other for various purposes in the literature. In contrast, this paper utilized FIS to convert each qualitative weathering degree data into quantitative data. These values were then classified as intervals that represent the four weathering grades. Because WD classes should be represented by intervals rather than a single value. In the follow-up phase of the study, the FIS outputs were used in the ANN analyses to develop an explicit neural network formulation to predict WD. Relevantly, the neural network toolbox (nntool) was used to build several neural networks in the MATLAB environment. The database was randomly divided into training (70/100), testing (15/100), and validating (15/100) parts. The most convenient ANN architecture obtained in this study was 3–5–1 (Fig. 5). Before the ANN analyses have been performed, the database was normalized using the following equation (Singh et al. 2012; Lawal and Idris 2019):

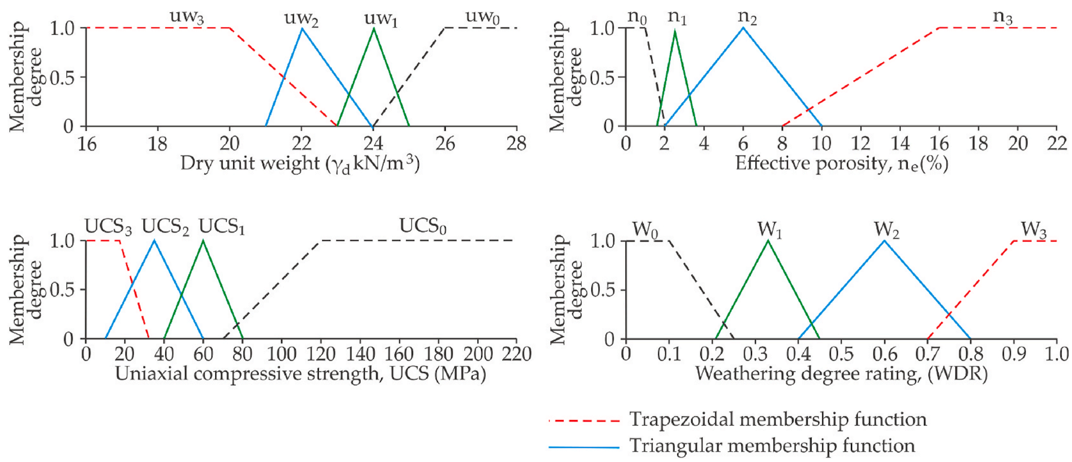

Fig. 4. Membership functions adopted in the FIS model.

Table 3
If-then rules.

Rules	Explanation
R1	If γ_d is uw_0 and n_e is n_0 and UCS is UCS_0 then WD is **W_0**
R2	If γ_d is uw_0 and n_e is n_1 and UCS is UCS_0 then WD is **W_0**
R3	If γ_d is uw_0 and n_e is n_2 and UCS is UCS_0 then WD is **W_0**
R4	If γ_d is uw_0 and n_e is n_1 and UCS is UCS_1 then WD is **W_0**
R5	If γ_d is uw_1 and n_e is n_1 and UCS is UCS_0 then WD is **W_0**
R6	If γ_d is uw_2 and n_e is n_1 and UCS is UCS_0 then WD is **W_0**
R7	If γ_d is uw_2 and n_e is n_2 and UCS is UCS_0 then WD is **W_0**
R8	If γ_d is uw_1 and n_e is n_1 and UCS is UCS_1 then WD is **W_1**
R9	If γ_d is uw_0 and n_e is n_2 and UCS is UCS_1 then WD is **W_1**
R10	If γ_d is uw_0 and n_e is n_0 and UCS is UCS_1 then WD is **W_1**
R11	If γ_d is uw_0 and n_e is n_0 and UCS is UCS_2 then WD is **W_1**
R12	If γ_d is uw_0 and n_e is n_2 and UCS is UCS_2 then WD is **W_1**
R13	If γ_d is uw_1 and n_e is n_2 and UCS is UCS_1 then WD is **W_1**
R14	If γ_d is uw_1 and n_e is n_0 and UCS is UCS_1 then WD is **W_1**
R15	If γ_d is uw_1 and n_e is n_0 and UCS is UCS_0 then WD is **W_1**
R16	If γ_d is uw_1 and n_e is n_1 and UCS is UCS_0 then WD is **W_1**
R17	If γ_d is uw_1 and n_e is n_2 and UCS is UCS_0 then WD is **W_1**
R18	If γ_d is uw_2 and n_e is n_2 and UCS is UCS_1 then WD is **W_1**
R19	If γ_d is uw_2 and n_e is n_2 and UCS is UCS_0 then WD is **W_1**
R20	If γ_d is uw_0 and n_e is n_1 and UCS is UCS_0 then WD is **W_1**
R21	If γ_d is uw_1 and n_e is n_1 and UCS is UCS_2 then WD is **W_1**
R22	If γ_d is uw_1 and n_e is n_0 and UCS is UCS_2 then WD is **W_1**
R23	If γ_d is uw_2 and n_e is n_1 and UCS is UCS_1 then WD is **W_1**
R24	If γ_d is uw_2 and n_e is n_1 and UCS is UCS_0 then WD is **W_1**
R25	If γ_d is uw_1 and n_e is n_2 and UCS is UCS_1 then WD is **W_1**
R26	If γ_d is uw_2 and n_e is n_2 and UCS is UCS_2 then WD is **W_2**
R27	If γ_d is uw_1 and n_e is n_1 and UCS is UCS_2 then WD is **W_2**
R28	If γ_d is uw_1 and n_e is n_2 and UCS is UCS_1 then WD is **W_2**
R29	If γ_d is uw_1 and n_e is n_2 and UCS is UCS_2 then WD is **W_2**
R30	If γ_d is uw_1 and n_e is n_1 and UCS is UCS_3 then WD is **W_2**
R31	If γ_d is uw_1 and n_e is n_2 and UCS is UCS_3 then WD is **W_2**
R32	If γ_d is uw_2 and n_e is n_2 and UCS is UCS_1 then WD is **W_2**
R33	If γ_d is uw_2 and n_e is n_3 and UCS is UCS_1 then WD is **W_2**
R34	If γ_d is uw_2 and n_e is n_3 and UCS is UCS_2 then WD is **W_2**
R35	If γ_d is uw_3 and n_e is n_2 and UCS is UCS_2 then WD is **W_2**
R36	If γ_d is uw_3 and n_e is n_2 and UCS is UCS_3 then WD is **W_2**
R37	If γ_d is uw_3 and n_e is w_2 and UCS is UCS_1 then WD is **W_2**
R38	If γ_d is uw_3 and n_e is n_3 and UCS is UCS_3 then WD is **W_3**
R39	If γ_d is uw_2 and n_e is n_3 and UCS is UCS_2 then WD is **W_3**
R40	If γ_d is uw_2 and n_e is n_2 and UCS is UCS_3 then WD is **W_3**
R41	If γ_d is uw_2 and n_e is n_3 and UCS is UCS_3 then WD is **W_3**
R42	If γ_d is uw_3 and n_e is n_3 and UCS is UCS_2 then WD is **W_3**

$$V_N = 2\left(\frac{x_i - x_{\min}}{x_{\max} - x_{\min}}\right) - 1 \tag{1}$$

where x_i is the relevant parameter to be normalized, x_{min}, and x_{max} are the minimum and maximum values in the database. The predicted WDR values were also denormalized using the following equation.

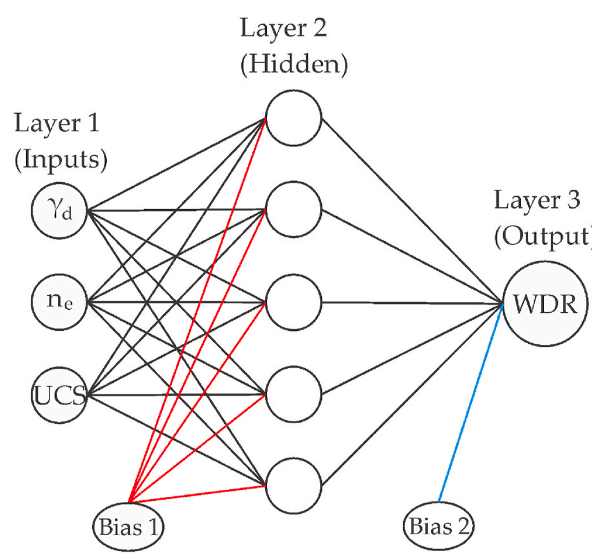

Fig. 5. ANN architecture adopted in this study.

$$x = 0.5(x_n + 1)(x_{\max} - x_{\min}) + x_{\min} \tag{2}$$

where x_{max} and x_{min} values are given in Table 2.

The neural network training was performed using a feedforward backpropagation algorithm with the Levenberg-Marquardt training function. In order to transmit the data through the neurons, the tangent sigmoid (tanh) function was utilized as given in the equation below.

$$\tanh = \frac{2}{1 + e^{-2x}} - 1 \tag{3}$$

For a better understanding and quantification of the WD, different rock properties (γ_d, n_e, and UCS) were used in this study (Fig. 5). Based on the above explanations, the ANN analyses were performed to estimate the WD of the andesitic rocks. Once the ANN has been trained, the predictive equations can be coded based on the weights and biases extracted from the ANN analyses. In this regard, the empirical model to predict the WDR values was derived using the following equation (Das, 2013; Lawal and Idris, 2019).

$$Y = f_{sig}\left\{b_0 + \sum_{k=1}^{h}\left[w_k \times f_{sig}\left(b_{hk} + \sum_{i=1}^{m} w_{ik} X_{i(N)}\right)\right]\right\} \tag{4}$$

where b_0 is the bias at the output layer, w_k is the connection weight between the kth neuron of the hidden layer and the single output neuron, b_{hk} is the bias at the kth neuron of the hidden layer, h is the number of neurons in the hidden layer, w_{ik} is the connection weight between the ith input variable and kth neuron of the hidden layer, $X_{i(N)}$ is the normalized input variable, f_{sig} is the sigmoid transfer function (i.e., tanh).

3. Results and discussion

3.1. Weathering degree ratings (WDRs)

There is a tendency to use sharp borders between successive WD classes (Hack and Price, 1997; Zorlu, 2008; Gökçeoğlu et al., 2009; Dağdelenler et al., 2011). However, a reasonable approach to represent WD would be to use various intervals. Consequently, predictive models should be constructed based on such intervals (e.g., WDR = 0–1). The practical importance of FIS is that computing uncertain or overlapping distributions of parameters does not have to be associated with a given (known) output with exact identifications (Mendel, 2001). After defuzzification, it finally estimates the WDRs for each sample within a given range (0–1). From this point of view, expert rules become prominent, and they operate the FIS system. This process may be declared time-consuming; however, it is more logical and provides consistent results because it is independent of the observed/predefined WD. In this context, the surface models obtained from the FIS analyses are given in Fig. 6. Accordingly, the FIS divides the surface models into specific weathering zones, illustrated with different colors in Fig. 6.

In this study, the estimated WDRs were classified, referring to such intervals for each WD class (W0–W3) as illustrated in Fig. 7. Only nine samples of 182 failed to match their assigned class (Fig. 7). It corresponds to a prediction error of 4.94% in the dataset. It is necessary to clarify that the nine samples represent the transition between successive WD classes. It is also likely that volcanic glass, which is a constituent of the rock matrix alters faster than any mineral as stated earlier by Colman (1982). Since the rock specimens in the database have different proportions of volcanic glass in the matrix, those with low glass content are less affected by the weathering-induced mechanical and physical breakdown. Yokota and Iwamatsu (1999) have also argued that the reaction of water with volcanic glass leads to changes in clay fraction and volume which will further promote the physical and mechanical damages. As a result, these samples can be predicted to have relatively lower WDRs.

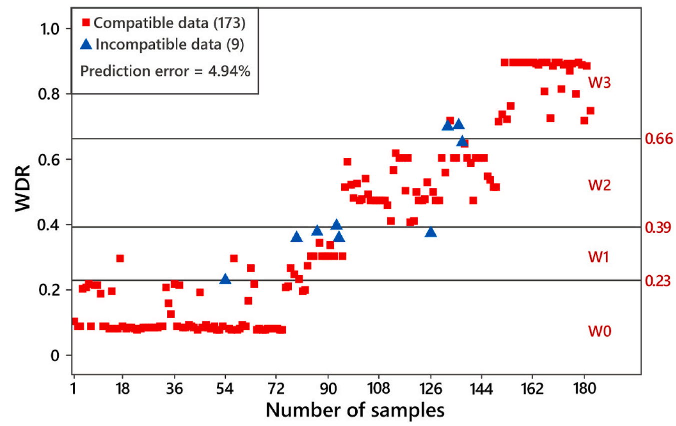

Fig. 7. Scatter plots for the estimated WDRs.

On the contrary, the relatively higher amount of glass in the matrix would cause the rock to have higher WDRs among the same rock group. Based on the scatter plots in Fig. 7, a quantitative classification of WDRs for andesitic rocks is given in Table 5.

3.2. Explicit neural network formulation

A combined application of FIS and ANN analyses is based on importing the WDRs derived from FIS that vary between 0 and 1 into the

Table 5
Weathering degree classification for andesitic rocks.

Weathering degree	WDR
W_0	≤0.23
W_1	0.23–0.39
W_2	0.39–0.66
W_3	≥0.66

The input parameters are the γ_d, $n_{e,}$ and UCS for the estimation of WDR.

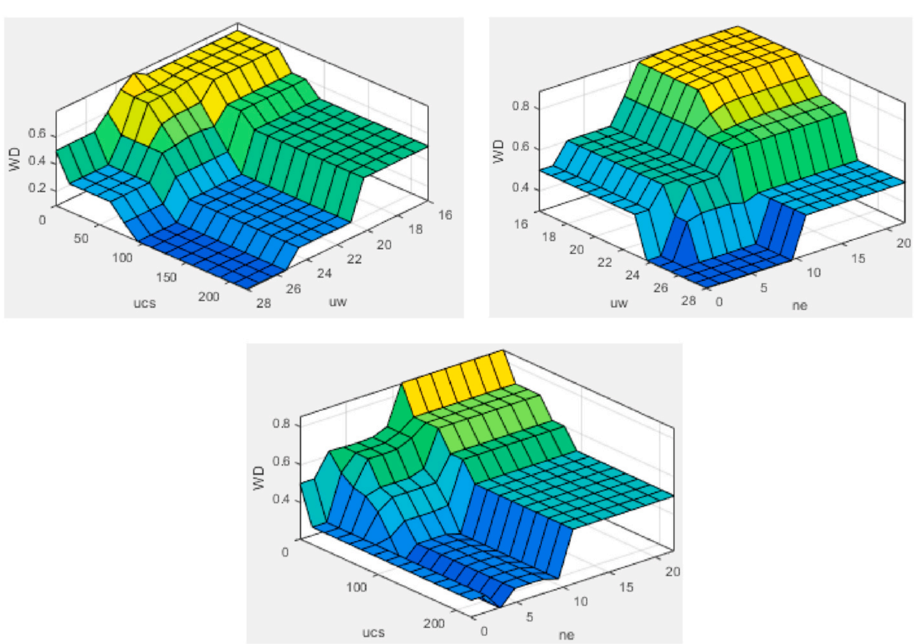

Fig. 6. Surface models obtained from FIS analyses.

ANN model. It is obvious that the proposed ANN model learned to accurately map the relationship between the γ_d, n_e, UCS and WDR (Fig. 8). The explicit formulation was derived as an outcome of the ANN model. The model assumes that the WDR is not a single value for one weathering grade class. This assumption makes the proposed model more reliable since there is some discrepancy between physical and mechanical properties of rocks belonging to the same WD class. However, it should be pointed out that the equation is valid for the ranges of the training set of four parameters n_e, γ_d, UCS, and WDR. As a result, the WDR can be calculated by the below equations.

$$WDR = 0.4094 \tanh\left(\sum_{i=1}^{5} A_i + 0.36209\right) + 0.4846 \tag{5}$$

$$A_1 = -2.3572 \tanh\left(0.78202^n\gamma_d - 4.5998^n n_e - 2.1588^n UCS - 4.8012\right) \tag{6}$$

$$A_2 = -0.48427 \tanh\left(-0.6138^n\gamma_d - 0.45297^n n_e - 0.21231^n UCS + 1.3715\right) \tag{7}$$

$$A_3 = 1.4907 \tanh\left(-0.33528^n\gamma_d + 1.3897^n n_e - 1.8132^n UCS - 2.0094\right) \tag{8}$$

$$A_4 = 1.4100 \tanh\left(0.66589^n\gamma_d + 2.3445^n n_e - 1.8642^n UCS + 3.042\right) \tag{9}$$

$$A_5 = -2.3730 \tanh\left(-0.45516^n\gamma_d + 4.1083^n n_e + 2.7912^n UCS + 4.7472\right) \tag{10}$$

To activate the proposed ANN equations, the inputs (γ_d, n_e, and UCS) should be normalized using the equations in Table 6. Afterward, Eqs. (5)–(10) will be implemented, and the resultant WDRs can be evaluated based on the proposed WD classification (Table 5). The formulization behind the established ANN model can provide a practical and user-friendly approximation to evaluate the WD for andesitic rocks.

The performance of the proposed ANN model was evaluated using the relationship between estimated and established WDRs. It is seen from Fig. 8 that the proposed ANN model has a high prediction capability ($R^2 = 0.98$). The average relative deviation was found to be below 1% (0.14%), indicating the precision of the ANN model. On the other hand, the ANN model can clearly distinguish the WD classes based on the proposed WDR intervals (Fig. 8)

4. Conclusions

Proper identification and interpretation of the WD of andesitic rocks would allow andesites to be used in broader engineering fields. Until recently, the weathering degree of andesitic rocks has not been investigated using soft computing methods, which are more advantageous than conventional regression models. The main limitation of the widely used soft computing algorithms such as ANN and ANFIS is that they are black-box models, and thus one cannot use the model in any other studies. To overcome this limitation, explicit neural network formulations for WD prediction were first developed in this study (Eqs. (5)–(10)). This study also contributes to the current literature by proposing a combined application of FIS and ANN. The FIS enabled quantifying the WDRs ranged between 0 and 1. These WDRs were then assigned to a WD class (W_0, W_1, W_2, W_3) for the proposed intervals. This assumption was thought to supplement and extend the practical use of the model. Thereby, it was demonstrated that representing the WDRs by a range is theoretically and practically a better approach than using a fixed and exact value for WD classes.

Table 6
Equations for the normalization of the inputs.

Equation	Inputs
$^n\gamma_d = 0.2304\gamma_d - 5.2673$	γ_d = 18.52–27.2 kN/m^3
$^n n_e = 0.0963 n_e - 1.0501$	n_e = 0.52–21.28%
$^n UCS = 0.0097 UCS - 1.0775$	UCS = 8–214.36 MPa

The introduced combined models yielded promising results in estimating the WD of andesitic rocks as a function of n_e, γ_d, and UCS. The proposed final ANN models yielded an R^2 of 0.98 and a relative deviation of 0.14%. The deviating samples between two successive WD classes may have a different amount of volcanic glass in the rock matrix, which relatively reduces the accuracy of the model. As a comprehensive database of andesitic rocks from different locations have been implemented, the proposed model can be described as a generalized predictive model for andesitic rocks.

The use of explicit formulation provided benefits that one can practically obtain WD class of andesitic rock materials with three inputs, and there is no need to construct a soft computing model. However, it should be used with several precautions, such as controlling the input parameter ranges for each WD class. Further investigations on different andesitic rock datasets would help to improve the reliability of the proposed model.

Funding statement

This research paper did not receive any specific grant from funding agencies in the public, commercial or non-profit sectors.

Authorship statement

Kadakci Koca, T (Corresponding author): Responsible for data collection, design, drafting, and revision of the manuscript, and interpretation of results.Köken, E: Responsible for implementation and testing of the algorithm, manuscript drafting, and interpretation of results.

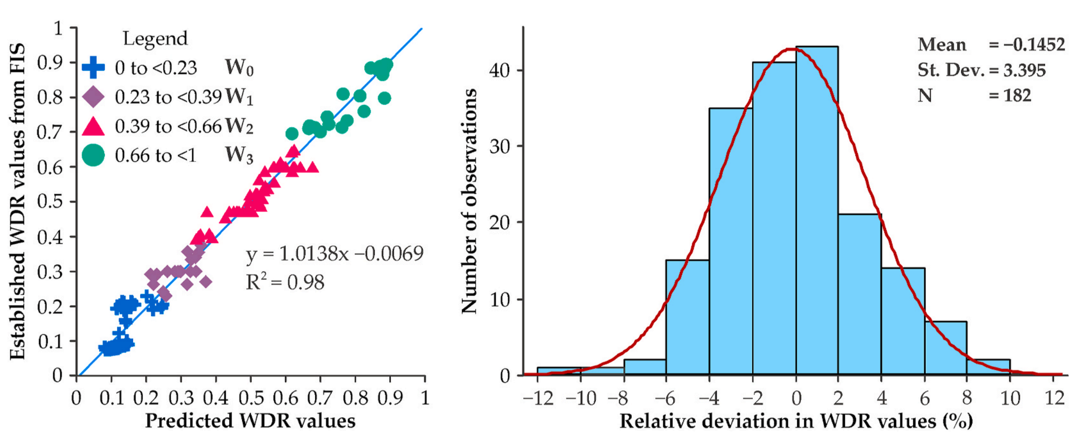

Fig. 8. Performance of the proposed equation systems obtained from the ANN.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

The authors are greatly indebted to Dr. Abiodun Ismail Lawal (Federal University of Technology, Akure) for his valuable contributions to the ANN analyses.

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