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Research Article

Modelling of the Elasticity Modulus for Rock Using Genetic Expression Programming

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In rock engineering projects, statically determined parameters are more reflective of actual load conditions than dynamic parameters. This study reports a new and efficient approach to the formulation of the static modulus of elasticity E_s applying gene expression programming (GEP) with nondestructive testing (NDT) methods. The results obtained using GEP are compared with the results of multivariable linear regression analysis (MRA), univariate nonlinear regression analysis (URA), and the dynamic elasticity modulus (E_d). The GEP model was found to produce the most accurate calculation of E_s. The proposed approach is a simple, nondestructive, and practical way to determine E_s for anisotropic and heterogeneous rocks.

1. Introduction

Strength and deformation features play an important role in the design of rock structures [1]. The elasticity modulus is an important parameter in understanding stress-strain behaviour and is one of the most mechanical characteristics of rocks in regarding their using area [2]. This parameter is decisive in tunnel project, rock destruction and drilling, slope consistency, pillar configuration, embankments, and many other civil and mining applications [3]. It has been used extensively for the analysis of structural deformations, creep, shrinkage, crack control, and so forth [4–6].

Either static or dynamic various numbers of methods are available for determination of deformation parameters. The static elasticity modulus (E_s) can be obtained from conventional laboratory procedures, for example, from the incline of tensile test stress-strain diagrams, but as they are generally time consuming and expensive even on a laboratory applications, the number of tests in many projects is limited. On the other hand, the dynamic elasticity modulus (E_d) can be determined from compression (V_p) and shear (V_s) wave velocities, and knowledge of the rock density (ρ) is based essentially on rapidly applied nondestructive loads; in many cases this requires simple and easy operations.

During the design of rocks inside structures, statically achieved parameters are preferred rather than those obtained by dynamic methods as the statically determined ones are more reflective of real loading situations [1]. The values of elastic constants often disagree with those determined by static laboratory methods. Hence, the true E_s is usually different from values determined by either static or dynamic methods. According to ASTM-D2845-08 [7], elastic constants are not to be calculated using procedures described in the test method for rocks with pronounced anisotropy. For these reasons, E_d measurements are not common in rock engineering projects. Most rock materials do not behave in completely linear elastic, homogenous, isotropic mode, and hence there is a difference between E_s and E_d. Dynamic test methods therefore supply data that are only meaningful for the designing stage in rock engineering [8].

Because of the advantages of E_d and the validity of E_s, many researchers have aimed to predict E_s from E_d using multivariable linear regression analysis (MRA). Some of these authors include [9–11]. According to these studies, the E_d determined is generally higher than E_s. MRA modelling in particular has been used for some time because it has the advantage of performing easy-to-use regression constants to facilitate estimation of the significance of various input variables and is established by precharacterization of the construction of a model with a limited number of linear or nonlinear equations.

Lama and Vutkuri [12] reported that E_d is greater than E_s by up to 300%. It must be appreciated that predicting E_s from E_d is ultimately an inverse problem. To cope with these limitations and challenges, several alternative soft computing techniques have been used considerably to model human activities in various areas of engineering. Learning from experience and deriving the information is one of the essential properties of soft computing techniques. Artificial neural networks, adaptive neurofuzzy inference systems, and fuzzy logic methods are commonly used in many engineering applications. A major disadvantage of these systems is that they are not able to provide practical prevision equations [4, 13]. To overwhelm the restrictions of these techniques, genetic programming (GP) and its variants, such as linear genetic programming (LGP) and gene expression programming (GEP), have been used in engineering applications in recent years. In civil engineering applications, GP, LGP, and GEP have been applied successfully to behavioural modelling of the elastic modulus of concrete [4, 14].

Engineers in different countries are keen on nondestructive testing (NDT) to assess rock properties. These types of tests are simple to conduct as they need less or no specimen preparation and the test device is also simple [15, 16]. NDT methods, ultrasonic pulse velocity (UPV), and rebound hammer (RN) testers among preferable methods are the most generally used in application to determine rock characteristics. A number of researchers, including [17–20], have studied the relationship between rock properties and NDT.

The present study mainly aimed to investigate the use of GEP in predicting E_s for rock materials. Application of the GP methods pointed out higher amount of nonlinear relationship between experimental and estimated values with high precision and comparatively low error. Because GEP put together the advantages of genetic algorithms (GA) and GP, it has verified to be an effective modelling instrument for solving complex real-world problems, and complex relationships between parameters affecting E_s can be modelled easily by using a GEP approach [21]. In contrast to dynamic elasticity, there is no definitive formulation for anticipating the E_s of rock. For this reason, the GEP approach is preferred to build empirical models. To build the model, E_s results of 317 specimens were used in training, testing, and validation. The data sets were derived from an experimental study performed as part of this project. Three main parameters that clearly influenced E_s were selected as input variables: compression wave velocity (V_p), Schmidt rebound hardness (RN), and rock density (ρ). The results obtained were compared with those of other approaches to demonstrate the superiority and practicality of the proposed approach.

2. Materials and Methods

Samples of the rock materials were collected from various locations, mostly in Turkey but also from various other regions of the world. The rock blocks consisted mainly of marble, limestone, and igneous and magmatic rock. The rock samples used in the research program were received in the form of cylindrical pieces of NX-sized cores. The specimen density (ρ) was calculated from their dimensions and weights at a temperature of 20 ± 3°C.

Table 1: Mechanical and physical features of rocks used in experiments.

	Min	Max	Mean	Standard deviation
ρ (g/cm^3)	1.91	3.24	2.65	0.28
V_p (km/s)	0.74	6.48	4.23	1.26
V_s (km/s)	0.48	5.13	2.71	0.99
RN	0.5	70.6	41.44	16.85
f_c (MPa)	1.32	183	72.34	39.60
E_s (GPa)	0.51	94	31.14	22.68

The velocities of compression (V_p) and shear (V_s) waves were recorded in cylindrical core samples applying the high-frequency ultrasonic pulse technique proposed by ASTM [7]. The Schmidt hammer rebound (RN) test method is used crustily to examine the strength and quality of rock and hardened concrete. There is a strong relationship between the RN and the uniaxial compressive strength (f_c) of rock. The RN values of the rock specimens were obtained using an N-type Digi-Schmidt 2000 apparatus according to the procedures described in ASTM C 805 [22]. At least 20 measurements were taken at different points on each mixture sample.

Rock's most important parameter is its compressive strength (f_c) as it was indicated earlier [3]. The f_c properties of rocks were determined related with standards proposed by ASTM D7012-14 [23]. At least five core samples from each rock were subjected to strength tests performed by a fully automatic, instrumented, and computer-controlled press machine. For determination of E_s, full bridged electrical resistance strain gauges were used. Two strain gauge rosettes, consisting of two gauges each, were bonded to the surface of each specimen at two directly opposite points located halfway between the specimen ends for the measurement of axial and circumferential strains, which were recorded at 1-s gaps performing a static data logger. The tangential E_s was calculated according to the stress-strain curves derived. The mechanical and physical properties of the rocks are presented in Table 1.

3. Regression Analysis

SPSS packet programming was used for statistical analysis. For modelling, multivariable linear (MRA) and univariate nonlinear regression analysis (URA) were applied. The reason to apply MRA is to detect simultaneously more independent variables that justify variations in the dependent variable. E_s is considered to be the dependent variable and the rock properties V_p, V_s, RN, f_c, and ρ are independent variables. MRA was performed to detect the relationships among five independent variables thought to be relevant to E_s.

Table 2: Summary statistics for the five models of multivariable linear regression analysis.

Model number	Independent variables that contribute to model	R^2	Std. error of estimate
1	V_p	0.570	14.88615
2	V_p, RN	0.654	13.37531
3	V_p, RN, ρ	0.683	12.82088
4	V_p, RN, ρ, f_c	0.691	12.67647

Table 3: Regression coefficient values for univariate nonlinear regression analysis.

Models	Independent variable			
	ρ	RN	f_c	V_p
Linear	0.518	0.356	0.409	0.570
Logarithmic	0.494	0.262	0.373	0.507
Inverse	0.463	0.071	0.094	0.350
Quadratic	0.548	0.356	0.419	0.576
Cubic	0.547	0.358	0.421	0.582
Compound	0.580	0.415	0.453	0.667
Power	0.589	0.530	0.613	0.719
S	0.588	0.282	0.299	0.639
Growth	0.580	0.415	0.453	0.667
Exponential	0.580	0.415	0.453	0.667
Logistic	0.580	0.415	0.453	0.667

Regression analyses were carried out using SPSS 16 statistical software, which offers a stepwise regression method. Stepwise regression provides insight into which independent variables are significant by identifying good (although not necessarily the best) subset models, resulting in considerably less computing time than would be required to calculate all possible regressions.

During the MRA and URA, 5 and 55 different models were created, respectively. Linear, logarithmic, inverse, quadratic, cubic, compound, power, S-curve, growth, exponential, and logistic models were formed and tested individually for nonlinear regression analysis. In these multivariable and univariate models, the highest regression coefficient (R^2) value is 0.69 for model 4 (Table 2) and 0.72 for the power-type model (Table 3), where V_p is an independent variable. The results of the multivariable and univariate regression coefficients (R^2) for these models exist to range within an plausible extent. Because of these results, there is no need to assess the validity of these models further.

4. Gene Expression Programming

GEP is a new evolutionary artificial intelligence method developed by Ferreira [24]. It is a strong evolutionary algorithm that includes both simple linear chromosomes of arranged length, similar to those performed in genetic algorithms (GA), and separated structures of different sizes and structures, similar to the parsing trees of genetic programming (GP). Its evaluation system for any type of knowledge mirrors that of biological evaluation and is encoded as a computer program in linear chromosomes of fixed length. In this method, a mathematical function identified as a chromosome with multiple genes is developed using the data presented to it. Although GEP mainly executes symbolic regression through most of the genetic operators of GA and GP, there are some differences between GA, GP, and GEP. GP represents it as nonlinear essences of different sizes and shapes (parsing trees) while any mathematical expression is adopted as a symbolic string of fixed length (chromosomes) in GA. However, in GEP it is encoded as simple strings of fixed length, which are subsequently expressed as expression trees of different sizes and shapes [25, 26]. One such gene, expression tree (ET), and its algebraic expression can be represented in Figure 1. For more detailed information, the reader is referred to Ferreira [24, 27]:

$$\text{Mathematical Equation: } \sqrt{(a-b)(c+d)}. \tag{1}$$

4.1. GEP Model. The principle in the development of GEP models was to generate a mathematical function for predicting E_s using only NDT methods (RN, V_p) and ρ. When selecting these variables, it has been noted that they are used in the estimation of E_d, which is provided by well-known methods to determine the deformation characteristics of materials. The widely used parameters in the determination of E_d are V_p, V_s, and ρ. Previous researchers have demonstrated that V_p and V_s [28, 29] as well as compressive strength and RN [30, 31] are highly correlated. Multicollinearity, a strong correlation between independent variables, might result in problems with the analysis. For example, variables do not contribute sufficiently to the model. Because of multicollinearity and the fact that measurements of V_s are more difficult than those of V_p, and because RN is a nondestructive technique that does not damage the sample, E_s is formulated as a function of V_p, RN, and ρ values of rocks.

The GEP model was developed using data sets of 317 rock specimens obtained from an experimental study. Both the practicing and examination data were randomly selected from these data. The numbers of experimental data sets used for initial practices and testing/validation in this model were 212 and 105, respectively. The parameters used in GEP model development are summarized in Table 4.

For GEP formulation, the fitness f_i of an individual program is measured by

$$f_i = \sum_{j=1}^{C_t} \left(M - \left| C_{ij} - T_j \right| \right), \tag{2}$$

where M is the range of selection, $C(i, j)$ is the value returned by the individual chromosome for performance case j (out of C_t fitness cases), and T_j is the target value for fitness case j. If $|C_{(ij)} - T_j|$ (the precision) is less than or equal to 0.01, then the accuracy is equal to zero, and $f_i = f_{\max} = C_t M$. In this case, $M = 100$ was used; therefore, $f_{\max} = 1000$. Since the system can find the optimal solution by itself, it can be considered as the advantage of this type of fitness function [24, 32, 33]. Next, the set of terminals "T" and the set of functions "F" used to create the chromosomes are chosen, namely, $T = \{V_p, \text{RN}, \rho\}$,

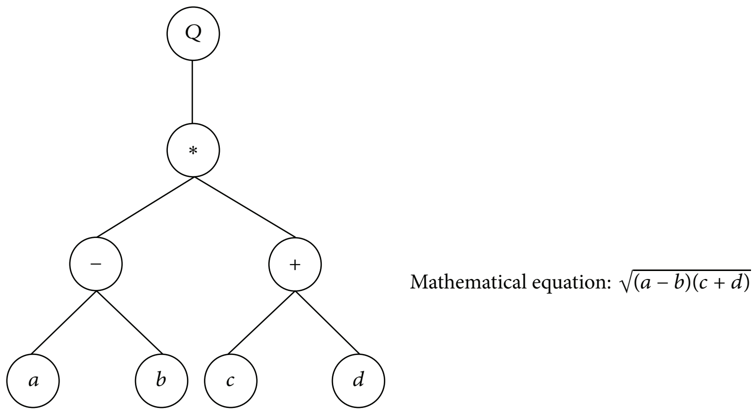

FIGURE 1: Example of GEP expression tree and mathematical equation.

and four basic arithmetic operators (+, −, ∗, /) and some basic mathematical functions (Sqrt, Cubic Root, 4Rt, Sub3, Exp, x^3, $1/x$, Ln) were used.

For choosing the chromosomal tree, that is, the length of the head and the number of genes, the GEP approach model initially used a single gene and two lengths of heads and increased the number of genes and heads, one after another, during each run, while monitoring the training and testing performance of each model. In the present study, after several trials, to achieve the best results the number of genes and length of heads were found to be 4 and 17, respectively. The sub-ETs (genes) were linked by multiplication.

Finally, a combination of all genetic operators (mutation, transposition, and crossover) was utilized as the set of genetic operators. Parameters used for training the GEP approach model are given in Table 1. Chromosome 20 was observed to be the best generation of individuals in predicting E_s. The definitive formulation of E_s based on the GEP approach model is given by

$$
\begin{aligned}
E_s = {} & \left\{ \frac{1}{\left[\sqrt[3]{\sqrt[4]{d_2 * d_1}} * c_1 * \left[(c_3/c_2) - (d_0/c_4)^3\right]\right] - \operatorname{Arctan}\left[(d_0 - c_2) * c_0\right]} \right\} \\
& * \left\{ \left[\sqrt[5]{d_2 - d_2^2}\right] - \left[\operatorname{Arctan}\sqrt[5]{\left[\operatorname{Arctan}(1/d_1)\right] + \left[d_2 + (d_0 - c_1)\right] * \operatorname{Ln}\sqrt[4]{d_1}}\right]\right\} \\
& * \left\{ d_0 - \left[d_1 - \left[c_4 * \left[d_0 - \sqrt[2]{c_1}\right] - \left[\left(\frac{d_2}{c_2} - d_0\right)\right]\right] * \left[(c_3 * d_2) - (d_0 * c_3)\right]^5\right]\right\} \\
& * \left\{ d_0 + \operatorname{Tanh}\left[\left[(c_2 * c_1) * (c_0 - d_2)\right] - d_1\right] * \left[\frac{1}{(d_0^2)^3}\right] * \left[\sqrt[2]{\left(\sqrt[2]{(d_2 * c_2)}\right)^5}\right]\right\}.
\end{aligned} \tag{3}
$$

The representation tree of the formulation is also shown in Figure 2, where d_0, d_1, and d_2 refer to ρ, RN, and V_p, respectively. The constants in the formulation are given in Table 5.

5. Results and Discussion

This study is supposed to find out possible the pertinence of GEP, MRA, and URA in predicting the E_s value of rocks, which has great significance in rock mechanics and foundation engineering. The developed models were compared with E_d. This part relatively presents the analysis results derived from these approaches and quantitative evaluations of the predictive capabilities of the models.

Of the 317 data sets, 212 were used for training the models and the 105 that were not used in training were used to test the models. To determine the success of the developed models, the regression coefficient (R^2), root-mean-square error (RMSE), and average absolute percentage error (MAPE) were used as criteria to assess compatibility between the experimental and predicted values. The statistical success of the developed models and E_d values is shown in Table 6.

The R^2 value relating the experimental and predicted data using the GEP model is 0.90, implying that the GEP model has good performance. On the other hand, the R^2 values of the MRA, URA (a power model where V_p is the independent variable), and E_d models are 0.68, 0.72, and 0.43, respectively.

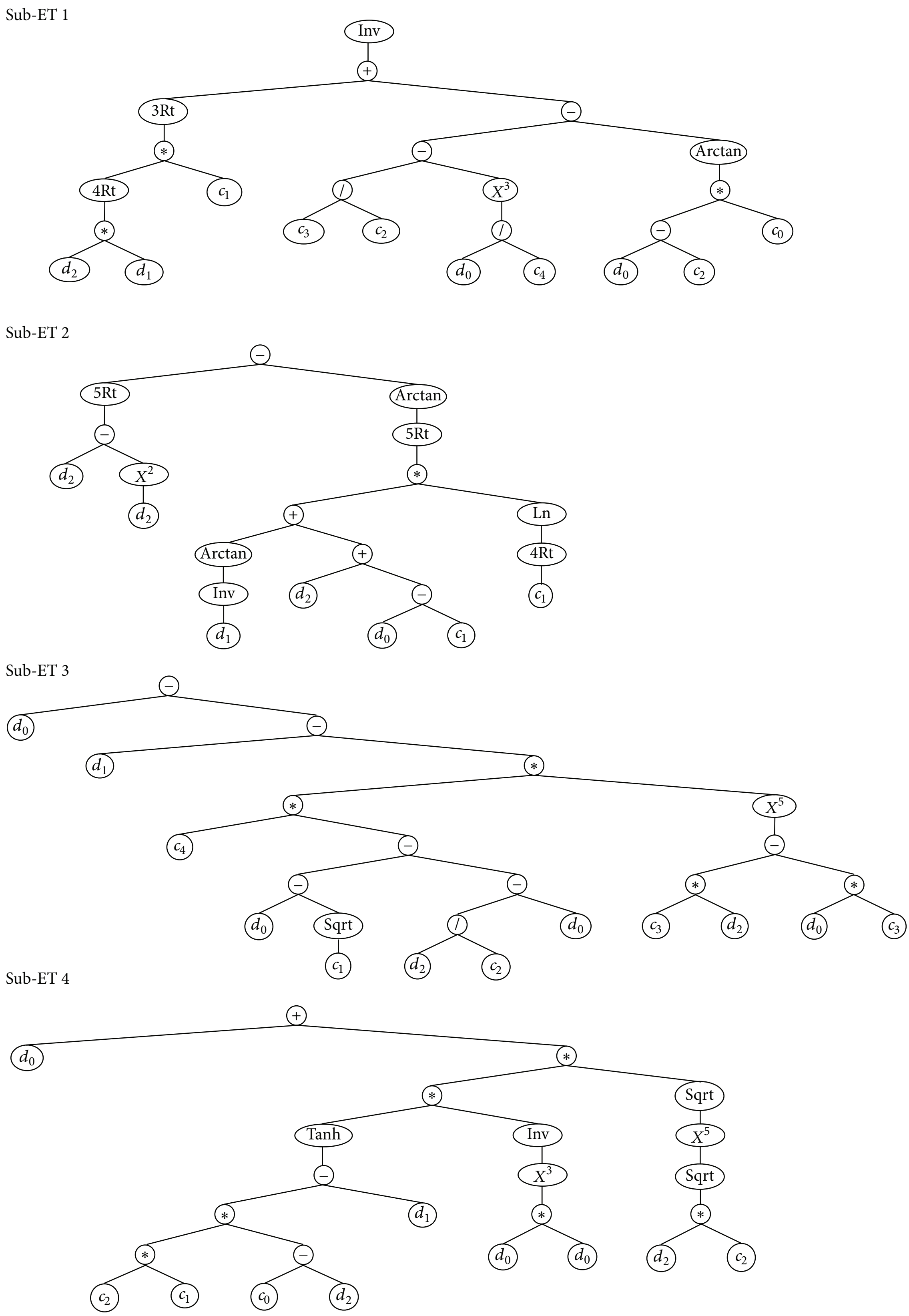

Figure 2: Expression tree for the GEP model.

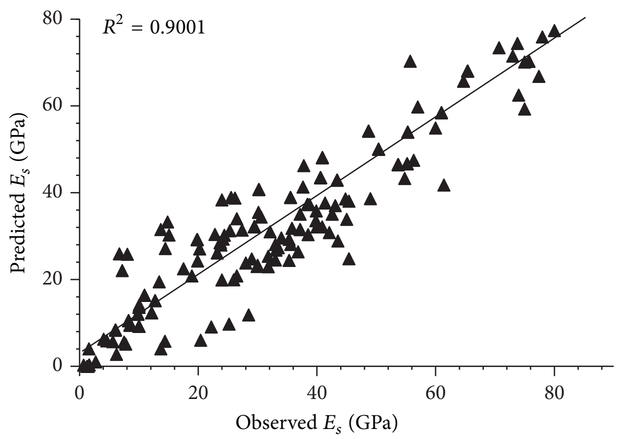

Figure 3: Measured versus predicted E_s for data used to train the GEP model.

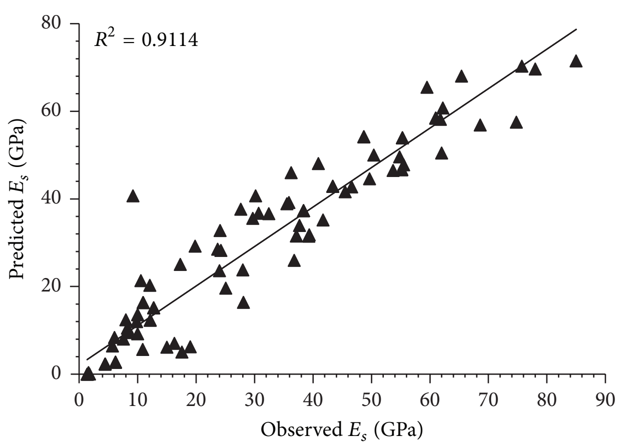

Figure 4: Measured versus predicted E_s for data used to validate the GEP model.

These values are not sufficient for confident validation of these models.

The E_s values predicted from GEP methods for training and testing are compared graphically with their experimental counterparts in Figures 3 and 4, respectively. As can be seen from these figures, there is a close compatibility between real and anticipated values.

Figure 5 shows the comparison between E_s and E_d values. As can be clearly seen in these figures, there is no relationship between the predicted and observed variables, and the results obtained by these methods are very different from the experimental results ($R^2 = 0.43$). In fact, for E_d in this study, even negative values are observed. As a result of the evaluation of these results, the GEP model was determined as the best applicable model for predicting E_s in comparison with MRA and E_d.

6. Conclusions

Findings of the presented study reported a new and efficient approach to the formulation of E_s using GEP with NDT and led to compare findings of MRA, URA, and E_d. The proposed model is empirical, and data for its development were derived from the experimental study conducted. It was shown that the GEP model considerably outperforms compared to other soft computing systems mentioned above. This was supported

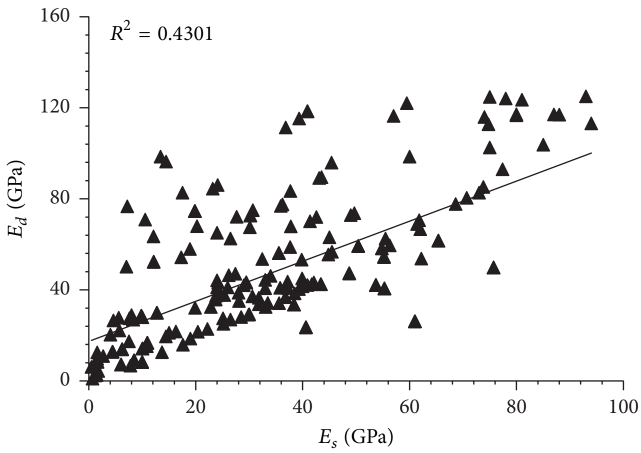

Figure 5: Comparison of static and dynamic elasticity.

Table 4: GEP parameters used for the developed model.

Parameter definition	GEP model
Program size	95
Literals	23
Number of generations	10,024,415
Arithmetic operators	+, −, ∗, /
Mathematical functions	Inv, sgrt, 3Rt, 4Rt, 5Rt, X^2, X^3, X^4, X^5, arctangent and hyperbolic tangent
Number of chromosomes	20
Head size	17
Tail size	18
Gene size	53
Number of genes	4
Linking function	Multiplication
Mutation rate	0.00138
Inversion rate	0.00546
One-point recombination rate	0.00277
Two-point recombination rate	0.00277
Gene recombination rate	0.00277
Gene transposition rate	0.00277

Table 5: Constants in the GEP model.

Constant	Sub-ET 1	Sub-ET 2	Sub-ET 3	Sub-ET 4
C_0	3.61	−4.31	7.18	5.91
C_1	11.19	6.00	16.88	6.98
C_2	3.07	5.51	5.85	10.29
C_3	3.20	5.81	−0.58	−6.25
C_4	−4.00	−8.86	−0.68	5.70

Table 6: Statistical parameters for predicting E_s.

	GEP model		Best MRA model	Best URA model	E_d
	Training	Validation			
R^2	0.90	0.91	0.68	0.72	0.43
RMSE	7.02	6.66	12.27	46.10	26.53
MAPE	5.44	4.97	87.96	98.49	102.56

and proven by statistical fitness criteria used for evaluating the models. The GEP model produced the highest R^2 value (0.90) and lower RMSE and MAPE values (7.02 and 5.44, resp.).

GEP is particularly suitable for predicting E_s values of rocks from anisotropic and heterogeneous materials in terms of calculating nonlinear functional relationships where classical methods cannot be easily performed. Moreover, with the use of GEP, E_s can be estimated without performing sophisticated and time-consuming laboratory tests. The proposed method is simple, does not damage the sample, and is sufficiently accurate to be recommended for use in practice.

Competing Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

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