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Prediction early age compressive strength of OPC-based geopolymers with different alkali activators and seashell powder by gene expression programming

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Abstract

In the present work, compressive strength of geopolymers produced by ordinary Portland cement, seashell powder and different alkali activators was predicted by gene expression programming design code. For constructing the models, 8 input parameters including the concentration of alkali solution, alkali binder to alkali solution weight ratio, alkali activator to cement+seashell powder weight ratio, oven curing temperature, water curing time, alkali solution type, alkali binder type and test trial number were considered. The output parameter was the compressive strength of the OPC+seashell powder based specimens. For collecting the data, 6 main factors each at 4 levels were considered for designing by the Taguchi method. A total of 32 series experiments (with 3 trials in each series) were conducted according to the L32 array proposed by the Taguchi method. According to the input parameters, the constructed models were trained and tested. From the total 96 obtained data, 70 sets were used for training and the remained 26 sets for testing the performance of the models. The results indicate that gene expression programming is a powerful tool for predicting the compressive strength of the geopolymers containing ordinary Portland cement, seashell powder and different alkali activators in the considered range with acceptable accuracy.

Keywords: Geopolymer; Seashell powder; Compressive strength; Gene expression programming

1. Introduction

Ordinary Portland cement-based (OPC-based) concrete is one of the most universal building materials. Its production and use have greatly increased during the last decades especially in emerging and developing countries. Although this material has outstanding structural performances, its production generates CO_2 accounting for up to 5% of anthropogenic emissions of this greenhouse gas. Alternative low-energy materials such as inorganic polymers (geopolymers) produced from natural minerals or inorganic wastes have attracted interest in the last three decades as possible more ecologically friendly cementitious materials. Aluminosilicate geopolymers consist of tetrahedral aluminate and silicate units linked by oxygen atoms, the negative charge of Al^{3+} in IV-fold coordination being compensated by ions such as Na^+, K^+, and Li^+. The silicate and aluminate units are randomly distributed in the structure in a range of Si environments, generally with a predominance of $SiQ^4(2Al)$ and $SiQ^4(3Al)$ [1].

The aluminosilicate source could be supplied from OPC like that was done in the previous work [2]. To activate the aluminosilicate source, an alkali binder such as sodium silicate (water glass) together with sodium hydroxide (NaOH) or potassium hydroxide (KOH) is used. While water glass is used as silicate source for production of aluminosilicate geopolymers [3], Williams and van Riessen [4] utilized anhydrous borax ($Na_2B_4O_7$) to produce borosilicate. This is the only work done till now by replacing alumina source with boron. Therefore, one may feel that this area could be improved by the further works.

In the previous work [2], compressive strength of geopolymers with ordinary Portland cement (OPC) as

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aluminosilicate source and NaOH + water glass (WG) as alkali activator was studied. It was reported that a specimen with NaOH concentration of 14 M, water glass to NaOH weight ratio equals to 1, alkali activator to cement weight ratio of 0.42, and curing at room temperature for 28 days has the highest strength (43.1 ± 3.0 MPa) in the considered procedure. In the present work, OPC again has been considered as aluminosilicate source. Seashell powder as a waste material was used to reduce the final cost. For alkali activation of the specimens, 4 different mixtures including NaOH + WG, NaOH + borax, potassium hydroxide (KOH) + WG and KOH + borax were used. To avoid conducting a huge number of experiments with repeated results, the Taguchi experiment design has been utilized with 6 main factors each at 4 levels. The Taguchi method suggested a L32 array similar to the previous work [2].

Soft computing techniques, including artificial neural networks (ANN), fuzzy logic (FL), neuro-fuzzy systems (FIS) and gene expression programming (GEP) can be used as an alternative to a physical model especially for complex nonlinear systems. ANNs are able to learn and generalize from examples and experience to produce meaningful solutions to problems. FL provides inference mechanisms that enable approximate reasoning and model human reasoning capabilities to be applied to knowledge-based systems [5]. Application of AAN, FL and FIS models for various properties of geopolymers have been rarely addressed in the literature except those were done in the previous works [6–11].

Genetic programming (GP) has begun to arise for the explicit formulation of the properties and application of engineering materials and methods [12]. Genetic programming offers many advantages as compared to classical regression techniques. Regression techniques are often based on predefined functions where regression analyses of these functions are later performed. On the other hand, in the case of GP approach, there is no predefined function to be considered. In this sense, GP can be accepted to be superior to regression techniques and neural networks. GP has proven to be an effective tool to model and obtain explicit formulations of experimental studies including multivariate parameters where there are no existing analytical models [13]. As authors' literature surveys, there are no or atleast limited work on predicting the compressive strength values of geopolymers by gene expression programming (GEP), a population-based evolutionary algorithm. Application of GEP in other engineering and scientific problems has been addressed in several works like the author previous one [13].

In the present study, compressive strength of geopolymers produced by ordinary Portland cement, seashell powder and different alkali activators has been designed by GEP. A total number of 96 data were obtained from the experiments. Among them, 70 sets were used for training and the remaining 26 for testing the performance of the models.

2. Experimental procedure

The used cementitious material in this work was OPC with the specific gravity of 1.78 g/cm^3. Its chemical composition has been illustrated in Table 1. Seashell powder as waste material was used in geopolymers specimens. The weight ratio of seashell powder to OPC + alkali activator was 30–70.

Two different alkali solutions including NaOH and KOH and 2 different alkali binders consisting of WG and borax with different mixing procedures were used as the solution part of the mixture. WG and borax were used without following modification, but NaOH and KOH were diluted to different concentrations before using. Totally, 4 different mixtures including NaOH + WG, NaOH + borax, KOH + WG and KOH + borax were used.

Six main factors for the Taguchi experiment design were alkali solution concentration, alkali binder to alkali solution weight ratio, alkali activator to cement + seashell powder weight ratio, oven curing temperature, and water curing time each at 4 levels. The 4 levels of each factor have been illustrated in Table 2. Taguchi experiment design was performed by Qualitek 4 software. The suggested design by Taguchi method for 6 factors at 4 levels is L32 array in accordance to Table 3.

Table 1
Chemical composition of OPC and WG (wt%).

Material	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	SO_3	Na_2O	K_2O	Loss on ignition
OPC	25.5	10.1	3.9	45.7	2.6	2.3	0.6	0.7	3.1

Table 2
The introduced levels for each factor in Taguchi experiment design.

Factors	Level 1	Level 2	Level 3	Level 4
Alkali solution concentration	(M)5	8	12	14
Alkali binder to alkali solution weight ratio	1	1.5	2	2.5
Alkali activator to cement weight ratio	0.4	0.45	0.5	0.55
	0.45	0.5	0.55	0.6
Oven curing temperature (°C)	25	40	70	90
Alkali activator type	NaOH + WG	KOH + WG	NaOH + borax	KOH + borax
Water curing regime (day)	1	2	3	7

Notes: In the third row, for alkali activator to cement weight ratio factor, the above and below data are used when alkali binder is WG and borax, respectively.

Table 3
Suggested experiment series by Taguchi method for 6 factors in 4 levels in this work.

Sample designation	Alkali solution concentration	Alkali binder to alkali solution weight ratio	Alkali activator to cement weight ratio	Oven curing temperature (°C)	Alkali activator type	Water curing regime (day)
G1	5	1	0.55	90	NaOH+WG	2
G2	5	1	0.4	25	NaOH+WG	1
G3	8	1.5	0.45	25	NaOH+WG	7
G4	8	1.5	0.5	90	NaOH+WG	3
G5	12	2	0.55	40	NaOH+WG	3
G6	12	2	0.4	70	NaOH+WG	7
G7	14	2.5	0.5	40	NaOH+WG	2
G8	14	2.5	0.45	70	NaOH+WG	1
G9	5	2	0.5	70	KOH+WG	3
G10	5	2	0.45	40	KOH+WG	7
G11	8	2.5	0.55	70	KOH+WG	2
G12	8	2.5	0.4	40	KOH+WG	1
G13	12	1	0.45	90	KOH+WG	1
G14	12	1	0.5	25	KOH+WG	2
G15	14	1.5	0.55	25	KOH+WG	3
G16	14	1.5	0.4	90	KOH+WG	7
G17	5	1.5	0.5	40	NaOH+borax	2
G18	5	1.5	0.55	70	NaOH+borax	1
G19	8	1	0.6	70	NaOH+borax	7
G20	8	1	0.45	40	NaOH+borax	3
G21	12	2.5	0.5	90	NaOH+borax	3
G22	12	2.5	0.55	25	NaOH+borax	7
G23	14	2	0.6	25	NaOH+borax	1
G24	14	2	0.45	90	NaOH+borax	2
G25	5	2.5	0.6	90	KOH+borax	7
G26	5	2.5	0.45	25	KOH+borax	3
G27	8	2	0.5	25	KOH+borax	2
G28	8	2	0.55	90	KOH+borax	1
G29	12	1.5	0.45	70	KOH+borax	2
G30	12	1.5	0.6	40	KOH+borax	1
G31	14	1	0.55	40	KOH+borax	7
G32	14	1	0.5	70	KOH+borax	3

Totally 32 series of geopolymer specimens with the condition illustrated in Table 3 were prepared for compressive strength tests. NaOH and KOH were diluted by tap water to have concentrations of 5, 8 12 and 14 M. The solution was left under ambient conditions until the excess heat had completely dissipated to avoid accelerating the setting of the geopolymeric specimens. WG and borax were mixed with NaOH and KOH solutions to produce 4 different alkali activators. Pastes were mixed by shaking for 5–10 min to give complete homogenization. The mixtures were cast in available 5 cm edge polypropylene cubic molds. At first, the final weight of the mortar (OPC+alkali activator) was determined. 30 wt% of the mortar was considered to be replaced by seashell powder. Initially, OPC was mixed by seashell powder (cementitious material) in dry conditions. After that, alkali activator was mixed bt cementitious materials. The mixing was done in an air-conditioned room at approximately 25 °C. The molds were half-filled, vibrated for 45 s, filled to the top, again vibrated for 45 s, and sealed with the lid. The mixtures were then precured for 24 h at room temperature (precuring time). After the precuring process, the samples and molds were placed in a water bath to prevent moisture loss and the carbonation of the surface. The curing regimes for each series of specimens were in accordance to Table 3. For the specimens cured in elevated temperatures (40, 70 and 90 °C), the time of oven-curing (2 h) was considered in water curing regime.

The compressive strength results of the produced specimens were conducted on the cubic samples using a YAW-300 automatic pressure testing machine. The tests were carried out 3 times on each series and the average strength values were reported.

3. Experimental results

The compressive strength acquired from 32 suggested experiments by Taguchi experiment design method has been illustrated in Fig. 1. The highest strength is related to G16 specimen with KOH concentration of 14 M, WG to KOH weight ratio of 1.5 and alkali activator to cement weight ratio of 0.4 which was oven cured at 90 °C and then water cured until 7 days. However, G6 specimen with NaOH concentration of 12 M, WG to NaOH weight ratio of 2.0 and alkali activator to cement weight ratio of 0.4 which was oven cured at 70 °C and then water cured until

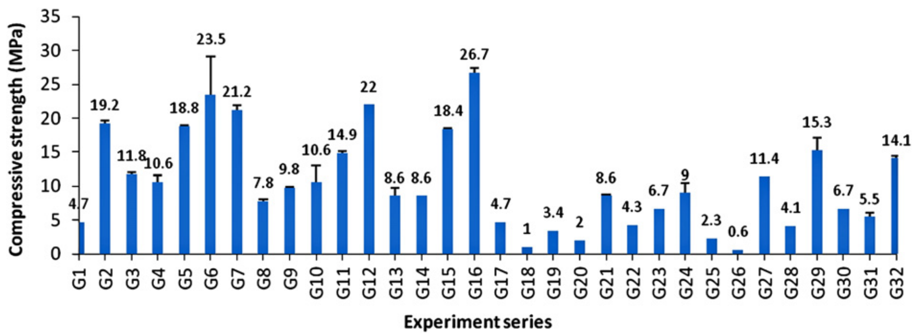

Fig. 1. Compressive strength of 32 series geopolymer specimens.

7 days has the highest strength by considering its error bar. These findings indicate that the traditional alkali activators (NaOH+WG and KOH+WG) were led to highest strength. Nevertheless, this may depend on the utilized aluminosilicate source. The other results indicate that for achieving high strength specimens, prolonged water curing regime and high concentration of alkali solution is required. In addition, curing the specimens in elevated temperatures may result in higher strengths. On the other hand, the lowest strength is related to G26 specimen with KOH concentration of 5 M, WG to NaOH weight ratio of 2.5 and alkali activator to cement weight ratio of 0.45 which was cured at room temperature and then water cured until 3 days. This indicates that for this type of aluminosilicate source, borax could not affect the final strength and once again, low concentration of alkali solution and low water curing regime with curing at room temperature resulted in the lowest strength.

4. Genetic programming and gene expression programming theory

Genetic programming (GP) approach is an extension to genetic algorithms proposed by Koza [14] who defines GP as a domain independent problem solving approach in which computer programs are evolved to solve, or approximately solve, problems based on the Darwinian principle of reproduction and analogs of naturally occurring genetic operations such as reproduction, crossover and mutation. GP reproduces computer programs to solve problems by executing the steps in Fig. 2 [15]. This figure is a flowchart showing the executional steps of a run of GP. The flowchart demonstrates the genetic operations in addition to the architecture chancing operations. Also, this flowchart demonstrates a two offspring version of the crossover operation.

GP approach evolves through the action of 3 basic genetic operators: reproduction, crossover and mutation. In the reproduction stage, a strategy must be adopted as to which programs should die. In the implementation, a small percentage of the trees with the worst fitness are killed. The population is then filled with the surviving trees according to accepted selection mechanisms, as explained following. Crossover swamps randomly selected parts of 2 trees to combine good information from the parents and to develop the fitness of the next generation, as shown in Fig. 3 [15]. Mutation protects the model against premature convergence and develops the non-local properties of the search, as shown in Fig. 4 [15]. Occasionally, one randomly selected node is replaced by another one from the same set, except itself.

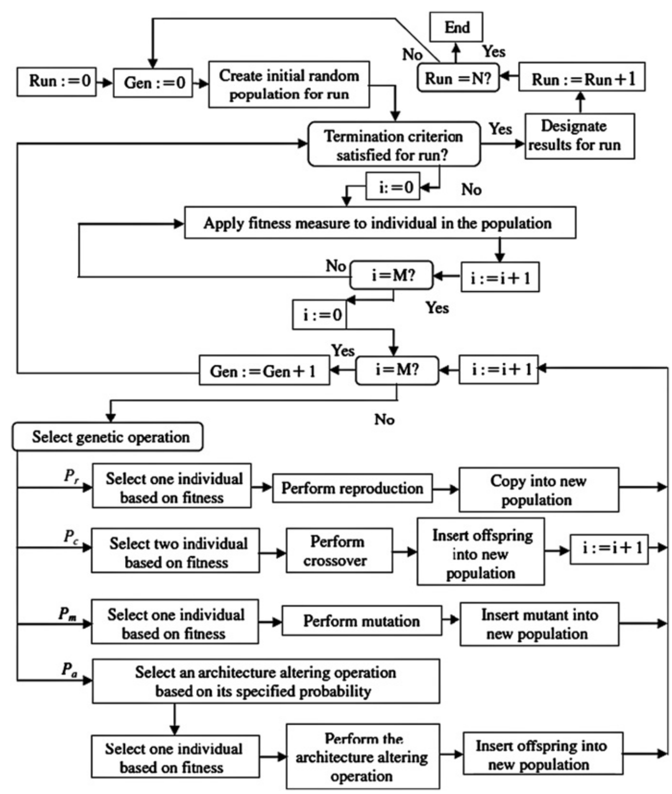

Fig. 2. Genetic programming flowchart [15].

In applying GP to a problem, there are 5 major preparatory steps. In order to solve a problem using Koza [14] states that it is necessary to specify the following:

(1) The set of terminals: a set of input variables or constants.
(2) The set of primitive functions: a set of domain specific functions used in conjunction with the terminal set to construct potential solutions to a given problem. For

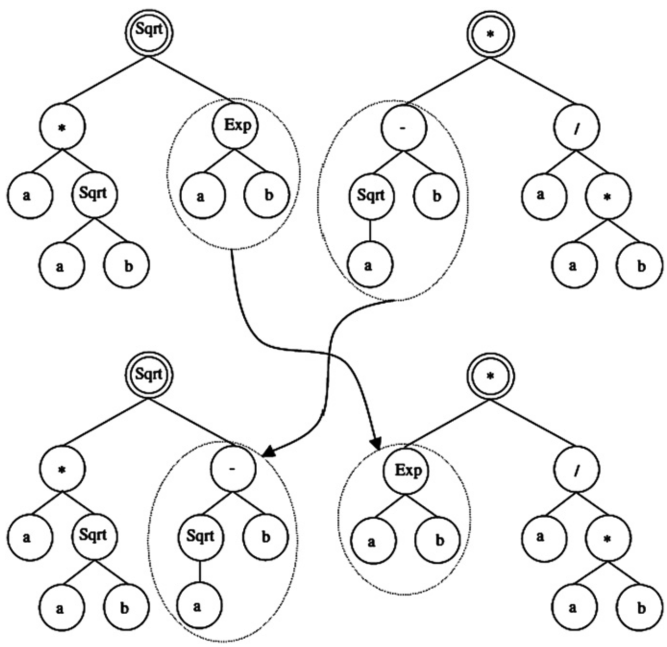

Fig. 3. Example of genetic programming crossover [15].

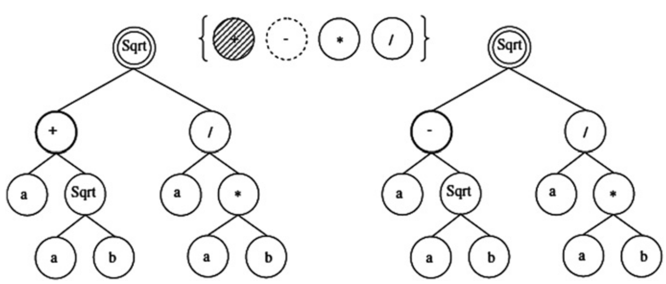

Fig. 4. Example of genetic programming mutation [15].

symbolic regression this could consist of a set of basic mathematical functions, while Boolean and conditional operators could be included for classification problems.

(3) The fitness measure: fitness is a numeric value assigned to each member of a population to provide a measure of the appropriateness of a solution to the problem in question.

(4) The parameters for controlling the run: this includes the population size and the crossover and mutation probabilities.

(5) The method for designating a result and the criterion for terminating a run: this is generally a predefined number of generations or an error tolerance on the fitness [14]. It should be noted that the first 3 components determine the algorithm search space, while the final 2 components affect the quality and speed of search [15].

The first major step in preparing to use GP is to identify the set of terminals. The terminals can be viewed as the inputs to the as-yet-undiscovered computer program. The set of terminals (along with the set of functions) are the ingredients from which GP attempts to construct a computer program to solve, or approximately solve the problem [15].

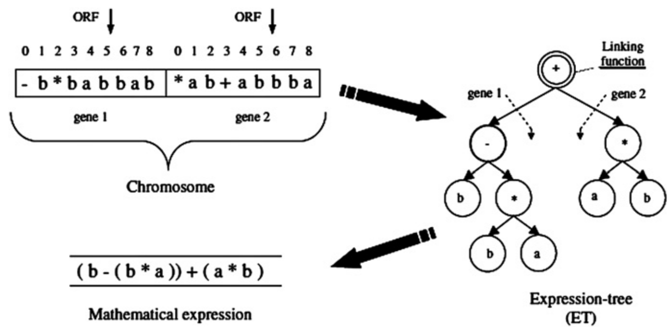

Fig. 5. Chromosome with 2 genes and its decoding in GEP [15].

The second major step in preparing to use GP is to identify the set of functions that are to be used to generate the mathematical expression that attempts to fit the given finite sample of data [15].

Gene expression programming (GEP) is a population-based evolutionary algorithm developed by Ferreira [16] and it is direct descendent of GP [14]. In GEP, individuals are encoded as linear strings of fixed size (genome), which are expressed later as non-linear entities with different sizes and shapes. These entities are known as expression trees (ETs). Usually, these individuals are composed by only 1 chromosome, which, in turn, can have 1 or more genes, divided in head and tail parts. ETs are the expression of a chromosome, and they undergo the selection procedure, guided by their fitness value, so as to generate new individuals. During reproduction, the chromosomes, rather than the respective ET, are modified by the genetic operator [15].

The genetic code operator is very simple where there exist one to one relationships between the symbols of the chromosome and the functions or terminals they represent. The rules also very simply determine the spatial organization of the functions and terminals in the ETs and the type of interaction between Sub-ETs [15]. That is the reason why 2 languages are used in GEP: the language of the genes and the language of ETs. A significant advantage of GEP is that it makes possible to infer exactly the phenotype given the sequence of a gene, and vice versa, which is termed as Karva language [15]. For example, an algebraic expression $[b\text{-}(b^{*}a)]+(a^{*}b)]$ can be represented by a 2 gene chromosome or an ET, as shown in Fig. 5 [15]. This figure shows how a chromosome with 2 genes is encoded as a linear string and how it is expressed as an ET. Note that, in this example, both genes have coding (expressed) and non-coding regions, just like the coding and non-coding sequences of biological genes [15].

5. Gene expression programming structure and parameters

In this study, as seen in Figs. 6 and 7, the expression trees of two different GEP approach models named GEP-I

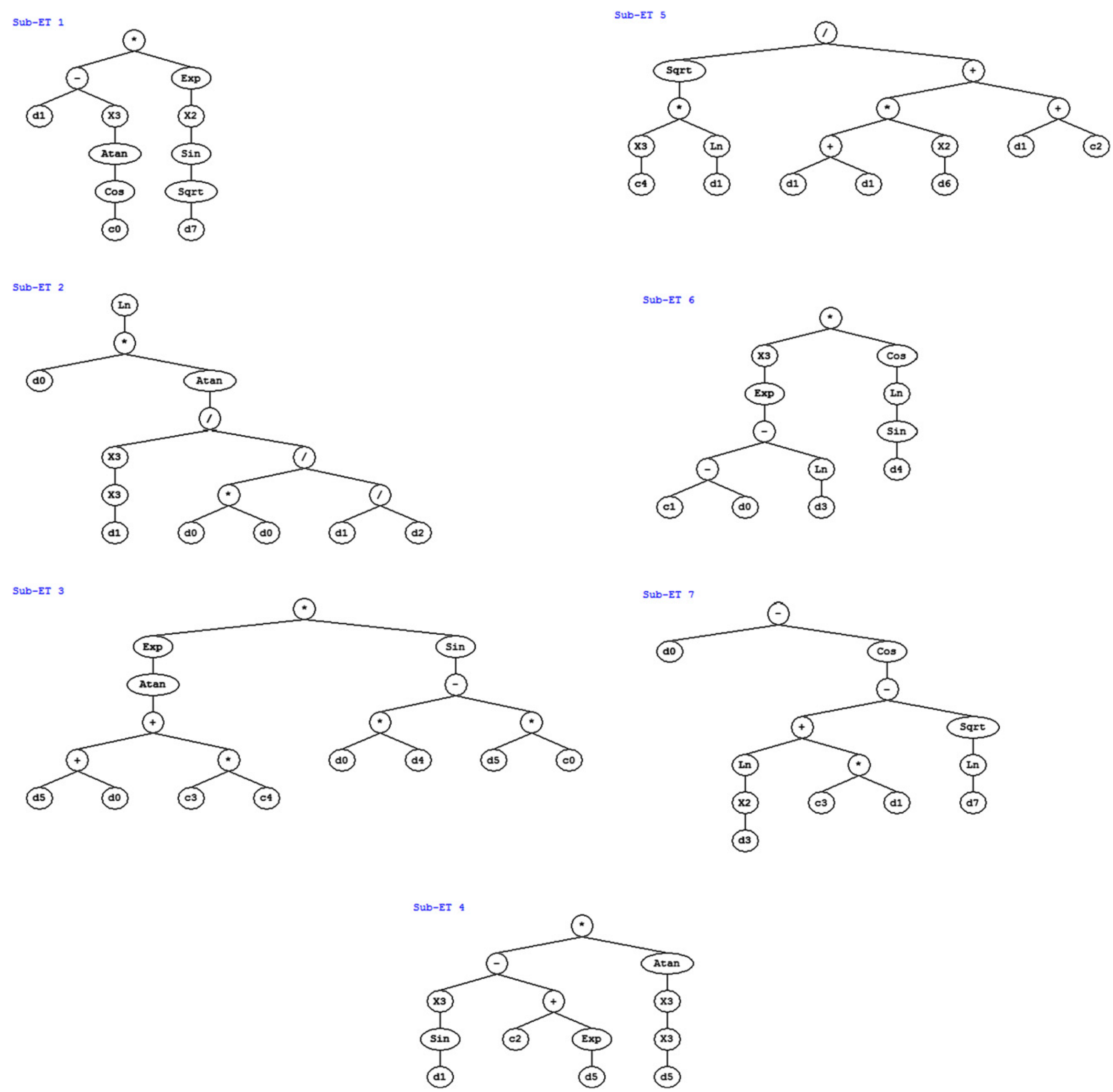

Fig. 6. Expression tree with 7 genes for predicting compressive strength of OPC+seashell powder based geopolymers with different alkali activators in GEP-I model.

and GEP-II were constructed for compressive strength (F_S) values of geopolymers. d0, d1, d2, d3, d4, d5, d6 and d7 in Figs. 6 and 7 represent the values for input layers which were the concentration of alkali solution (C), alkali binder to alkali solution weight ratio (W), alkali activator to cement+seashell powder weight ratio (A), oven curing temperature (T), water curing time (t), alkali solution type (AS), alkali binder type (AB) and test trial number (TN) were considered. Table 4 shows the range of each input parameters and that of output parameter. In GEP-I and GEP-II, the number of genes used were 7 and 6 genes (Sub-ETs), and linking function used were addition and multiplication, respectively. In training and testing of the GEP-I and GEP-II approach models constituted with 2 different Sub-ETs and linking function C, W, A, T, t, AS, AB and NT were employed as input data and F_S as independent output data. Among 96 experimental sets collected from the literature, 70 sets were randomly chosen as a training set for the GEP-I and GEP-II modeling and the remaining 26 sets were used as testing the generalization capacity of the proposed models.

For this problem, firstly, the fitness, f_i, of an individual program, i, is measured by [15]

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

where M is the range of selection, $C_{(i,j)}$ is the value returned by the individual chromosome i for fitness case j (out of C_t fitness cases) and T_j is the target value for

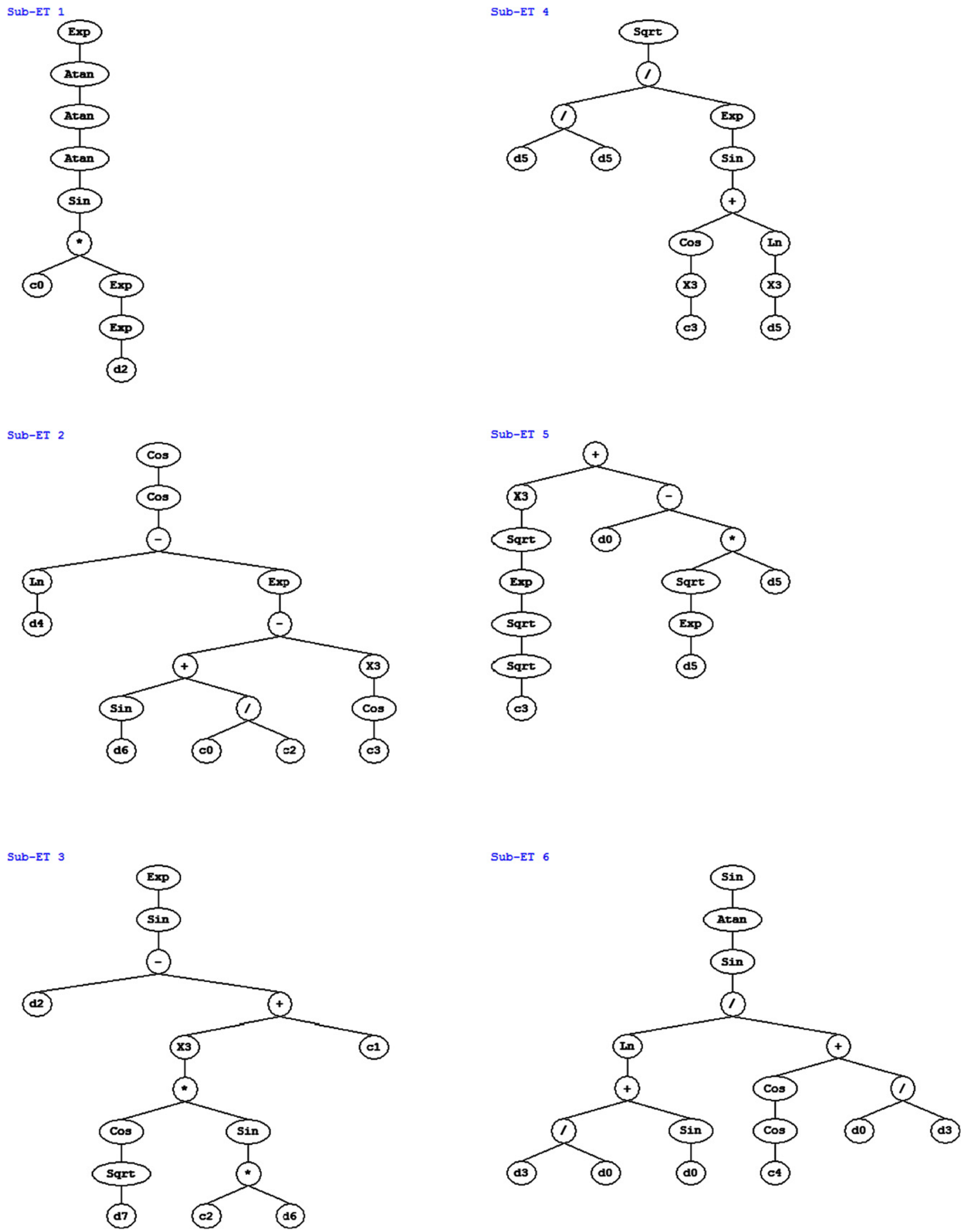

Fig. 7. Expression tree with 6 genes for predicting compressive strength of OPC+seashell powder based geopolymers with different alkali activators in GEP-II model.

Table 4
The range of the input parameters in GEP models.

Input	Range
Alkali solution concentration (M)	5–14
Alkali binder to alkali solution weight ratio	1–2.5
Alkali activator to cement weight ratio	0.4(0.45)–0.55(0.6)
Oven curing temperature (°C)	25–90
Water curing regime (day)	1–7
Alkali solution type[a]	1–2
Alkali binder type[b]	1–2
Test trial number	1–3
Compressive strength (MPa)	0.6–28.6

Notes: The initial data are used when alkali binder is WG and the data in parenthesis are used when borax is used as alkali binder.
[a]1 was used for NaOH and 2 for KOH.
[b]1 was used for WG and 2 for borax.

Table 5
Parameters of GEP approach models.

Parameter definition		GEP-I	GEP-II
P1	Chromosomes	30	40
P2	Head size	10	12
P3	Number of genes	7	6
P4	Linking function	Addition	Multiplication
P5	Constants per gene	5	4
P6	Weight of functions	7	7
P7	Mutation rate	0.044	0.044
P8	Inversion rate	0.1	0.1
P9	One-point recombination rate	0.3	0.3
P10	Two-point recombination rate	0.3	0.3
P11	Gene recombination rate	0.1	0.1
P12	Gene transposition rate	0.1	0.1

fitness case *j*. If $|C_{(ij)}-T_j|$ (the precision) is less than or equal to 0.01, then the precision is equal to zero, and $f_i = f_{max} = C_t M$. In this case, $M=100$ was used, therefore, $f_{max}=1000$. The advantage of this kind of fitness functions is that the system can find the optimal solution by itself [15].

Afterwards the set of terminals T and the set of functions F to create the chromosomes are preferred, namely, $T=\{C, W, A, T, t, \text{AS}, \text{AB}, \text{NT}\}$ and 4 basic arithmetic operators $(+, -, *, /)$ and some basic mathematical functions (Sqrt, x^2, x^3, Exp, ln, sin, cos, Arctan) were used.

Another major step is to choose the chromosomal tree, i.e., the length of the head and the number of genes. The GEP-I and GEP-II approach models initially used single gene and two lengths of heads, and increased the number of genes and heads, one after another during each run, and monitored the training and testing sets performance of each model [15]. In this study, for the GEP-I and GEP-II approach models observed the number of genes 7 and 6, and length of heads 10 and 12, respectively. In addition, for the GEP-I and GEP-II approach models determined the linking function addition and multiplication, respectively.

Finally, a combination of all genetic operators (mutation, transposition and crossover) was utilized as set of genetic operators. Parameters of the training of the GEP-I and GEP-II approach models are given in Table 5. For the GEP-I and GEP-II approach models, chromosome 30 and 40 were observed to be the best of generation individuals predicting the compressive strength values of geopolymers. Explicit formulations based on the GEP-I and GEP-II approach models for voltage were obtained by

$$F_S = f(C, W, A, T, t, \text{AS}, \text{AB}, \text{NT}) \tag{2}$$

The related formulations could be obtained by the procedure shown in Fig. 4 [15].

6. Predicted results and discussion

In this study, the error arose during the training and testing in GEP-I and GEP-II models can be expressed as absolute fraction of variance (R^2), the absolute percentage error (MAPE) and the root mean square error (RMSE) which are calculated by Eqs. (3)–(5), respectively [15]:

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2} \right) \tag{3}$$

$$MAPE = \frac{1}{n} \sum_i \left| \frac{t_i - o_i}{t_i} \right| \times 100 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_i (t_i - o_i)^2} \tag{5}$$

where t is the target value, o is the output value and n is the number of data sets in each of training and testing phases.

The corresponding equations for predicting compressive strength of the considered geopolymers in GEP-I and GEP-II models could be presented as Eqs. (6) and (7), respectively:

$$\begin{aligned} F_S(\text{GEP-}I) = {} & (W-0.09)\text{Exp}\left(\sin^2\sqrt{NT}\right) \\ & + \ln\left(C.\text{Arctan}\left(\frac{W^9}{C^2}A\right)\right) \\ & + \text{Exp}(\text{Arctan}(C+AS-7.98))\sin(Ct-1.45AS) \\ & + \left(\sin^3(W)-\text{Exp}(AS)+1.09\right)\text{Arctan}\left(AS^9\right) \\ & + \frac{\sqrt{13.1\ln(d1)}}{2WAB^2} + W - 7.98 + \text{Exp}^3(9.02-C-\ln(T)) \\ & \times\cos(ln(\sin(t))) + C - \cos\left(\ln\left(T^2\right) - 3.67W - 0.5\ln(NT)\right) \end{aligned} \tag{6}$$

$$\begin{aligned} F_S(\text{GEP-II}) = {} & \text{Exp}(\text{Arctan}(\text{Arctan} \\ & \times(\text{Arctan}(\sin(-6.64\text{Exp}(\text{Exp}(A)))))) \\ & \times\cos(\cos(\ln(t)-\text{Exp}(\sin(AB)+0.2)-0.2)) \\ & \times\text{Exp}\left(\sin\left(A+2.06-\left(\cos\sqrt{NT}\sin(-8.02AB)\right)^3\right)\right) \\ & \times\left(\text{Exp}\left(\sin\left(\ln\left(dAS^3\right)-0.07\right)\right)\right)^{-0.5} \\ & \times\left(7.64+C-AS\sqrt{\text{Exp}(AS)}\right) \end{aligned}$$

$$\times\sin\left(\text{Arctan}\left(\sin\left(\frac{\ln\left(\frac{T}{C}+\sin(C)\right)}{\frac{C}{T}+0.94}\right)\right)\right) \quad (7)$$

All of the results obtained from experimental studies and predicted by using the training and testing results of GEP-I and GEP-II models are given in Fig. 8a and b, respectively. The linear least square fit line equation, R^2, MAPE and RMSE values were also shown in the figure for the training and testing data. As it is visible in Fig. 8, the values obtained from the training and testing in GEP-I and GEP-II models are very close to the experimental results.

As shown in Fig. 7a and b, the predicted results from models are compared to the experimental results for training, testing and validation sets, respectively. The training set results proved that the proposed models have impressively well learned the non-linear relationship between the input and the output variables with high correlation and comparatively low error values. Comparing the GEP-I and GEP-II approach models prediction with the experimental results for the testing and training stages demonstrates a high generalization capacity of the proposed models and comparatively low error values. All of these findings exhibit a successful performance of the models for predicting compressive strength of OPC-based geopolymers in training and testing stages. The result of testing phase in Fig. 7 shows that the GEP-I and GEP-II models are capable of generalizing between input and output variables with reasonably good predictions.

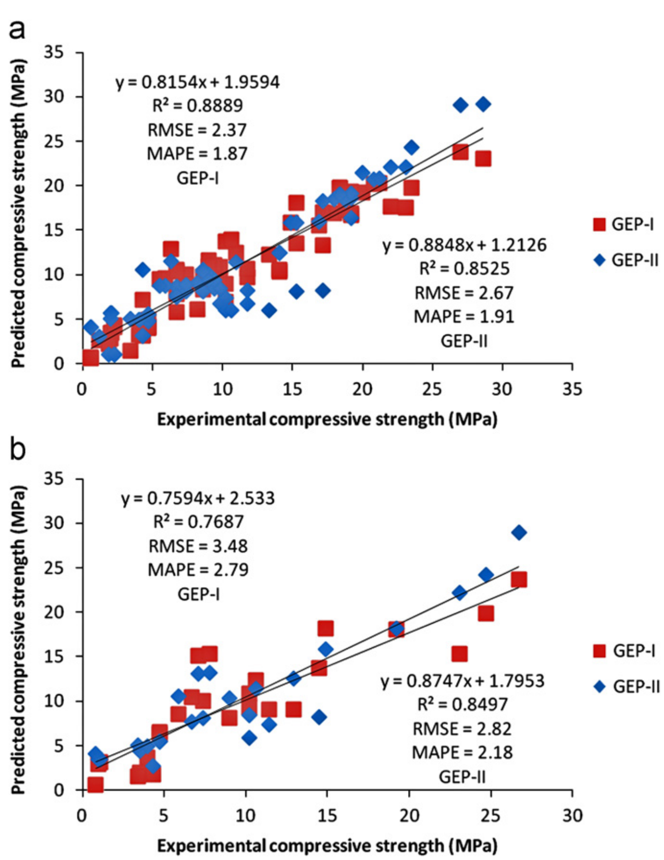

Fig. 8. The correlation of the measured and predicted compressive strength values of geopolymers in (a) training and (b) testing phase for GEP models.

The performance of the GEP-I and GEP-II models is shown in Table 3. The best value of R^2, and the minimum value of MAPE and RMSE are 0.8889, 1.87 and 2.37, respectively, all for training set in GEP-I model. The minimum value of R^2 and the maximum value of MAPE and RMSE are 0.7687, 2.79 and 3.48, respectively, all for testing set in GEP-I model. All of R^2, MAPE and RMSE values show that the proposed GEP-I and GEP-II models are suitable and can predict compressive strength values of geopolymers very close to the experimental values.

7. Conclusions

This study reports a new and efficient approach for the formulation of compressive strength of geopolymers produced by OPC, seashell powder and different alkali activators. Two different GEP-I and GEP-II approach models are proposed in order of compressive strength values of geopolymers. The proposed models are empirical and based on experimental results conducted on 32 series of specimens. The models developed in this study are used to be the number of genes 6 and 7, and the linking function multiplication and addition, respectively. All of the results obtained from the models show excellent agreement with experimental results. The statistical values of R^2, MAPE and RMSE have shown this situation. It was found that GEP can be an alternative approach for the evaluation of the compressive strength values of geopolymers. Comparison between GEP in terms of R^2, MAPE and RMSE showed that GEP models are capable to predict suitable results for compressive strength values.

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