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Modeling Compressive Strength of Lightweight Geopolymer Mortars by Step-Wise Regression and Gene Expression Programming

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ABSTRACT

This article presents a comprehensive study aimed at developing suitable mathematical models for the prediction of compressive strength of lightweight geopolymer mortar (LWGM) with different types and amounts binders with different curing regimes. Lightweight pumice aggregate, alkali activated powder materials are the main components of geopolymer binder. From the experimental study 306 data samples were obtained and these were used to derive explicit formulas for estimation of the compressive strength of LWGMs. Two methods are used to produce the models. The first is the simplified linear step-wise regression, while the second method is the genetic expression programming. Step-wise regression is a statistical tool that uses the impact of each factor to evaluate its effect on the equation. This impact is calculated based on the probability effect based on the F-distribution and the null-hypothesis. The default value of probability that refers to the significance of each factor is 0.05. Thus, the software calculates the probability of each of the independent variables and includes only those with probability values less than 0.05. Based on the included independent variables, simplified linear regression equation is introduced. The genetic programming on the other hand, is much more sophisticated method that uses the principles of gene evolution. The modeling is separated for each type of binder. Thus, two sets of formulas are obtained from each modeling, one for the granulated blast furnace slag -based LWGM, while the second is for the fly ash-based LWGM. These models revealed that genetic algorithm based modeling has a reliable potential for estimating the strength of LWGMs.

Keywords:
Geopolymer; Ground granulated blast furnace Slag; Fly ash; Lightweight Mortar; Step-Wise Regression; Genetic Modeling

INTRODUCTION

The great need for concrete results in depletion of huge quantities of cement. This causes a manufacture of equal amount of cement with an excessive amount of carbon dioxide emissions. CO_2 emissions from cement production are an important factor causing air pollution. The risk of ecological imbalance should also be taken into account because of the continuous consumption of natural resources. Greenhouse gas emissions from cement production are estimated to be 6-7% of the total [1,2].

Geopolymer, an innovative eco-friendly inorganic binder material obtained using industrial waste powders, can be taken into account as an alternative binder to the cement based system. There are lots of aluminosilicate based materials available in nature. Moreover, plenty of them are obtained from industrial by products. Hence, the utilization of these substances as binding agents has gained more significance for the construction sector. Therefore, intensive works have been performed to examine the features of composite materials incorporating geopolymer binder [3-6]. Besides, the development of hybrid geopolymer-based materials has been of a critical importance, as well, recently [7-9]. The most commonly used aluminosilicate substance in casting of geopolymer based concrete is FA, GGBFS and calcined kaolin [10-13]. Amongst those, FA and GGBFS are waste materials which can be used as substitutional cementitious materials for the concrete. Due to high CaO content more than 30%, GGBFS provides the formation of calcium silicate hydrate (C-S-H) gel-like structure in geopolymer composites as a result of chemical effect of alkali activators [14-19]. However, with the activation of fly ash by alkalis in order to form the amorphous inorganic polymers, F type FA is commonly desired for the geopolymer production due to provision of a reasonable setting behavior and strength development. The dosage and type of alkali activator is one of governing factors on properties of the gel and its formation [20]. Sodium silicate and NaOH are the most used activating solutions in geopolymer [21 - 24].

Some recent studies have demonstrated that various alkali activators based on sodium silicate and NaOH are useful in improving the mechanical properties of geopolymers containing industrial by-products [25-28]. The glassy nature of the GGBFS phase allows the alkaline to be activated more easily than FA. The presence of a larger crystal phase in FA requires higher temperatures for the accelerated reaction [29]. GGBFS addition to the system has been shown to result in a significant increase in the strength of FA-based geopolymer binders [30, 31].

Going back to the end of 1980's and the beginning of 1990's, the Genetic Algorithms (GAs) and later the Genetic Programming were developed as new evolutionary techniques. The genetic programming is simply the evolution and optimum solving of computer programs (research problems) of domain-independent-subjects from the Darwinian principles, namely, gene survival, reproduction, and evolution. Both genetic alghorithms and genetic programming techniques use only single type of individuals or entity to formulate both the genome and phenome types of the problem. In biology, the genome refers to the chromosome that carries all features of the entity, while the phenome is the visualized shape of that entity (the body). In genetic programming, the chromosomes are the individuals, which are fixed-length strings of linear form, while the individuals of GP are parse-trees of nonlinear different shapes and different lengths. The gene expression programming (GEP) on the other hand, uses the two forms, where fixed-length linear-strings are used to encode the individuals during the processing phase. These codes are then translated to nonlinear entities of different shapes and sizes in the post processing phase, which are simplified expression trees. Thus, GEP translates the language of chromosomes into a simple language of expression trees [32].

In GEP, different numbers of different-length and shape and multi-gene chromosomes are used to code the variables of the problem need to be solved. In addition to the main variables of the problems, the program defines constants and mathematical expressions as parts of these chromosomes. The mathematical expressions include all types of possible mathematical operations such as addition, subtraction, multiplication, division, square or higher order roots, squaring or higher powers, logarithms, exponentials, trigonometric functions, and others. In the start of the evolution process, a fitness function is chosen to evaluate the accuracy of the solution and the errors. This fitness is evaluated at the first step for a random generation. In the subsequent steps, the individuals with best fitness are selected (survived individuals) for reproduction and development of the next generation. The development of each next generation carried out by carrying some or all of several randomly selected operations on the survived (selected based on best fitness) chromosomes and genes from the previous generation. These reproduction operations include replication of survived genes, mutation, partial or gene transportation, and partial or gene recombination. This process continues one generation by another for several hundreds, thousands, or millions of generations until the best fitness of the solution is obtained. The flowchart of the GEP process is illustrated in Fig.1.

Estimation of a dependent variable can be made with the help of mathematical equation obtained by multiple

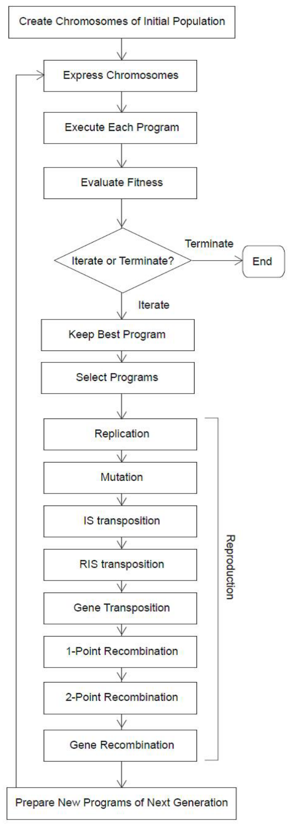

Figure 1. Flowchart of GEP

linear regression analysis. Stepwise regression is a statistical technique of adjusting regression models in which the choice of predictive variables is carried out by an automatic procedure. In each step, a variable is considered for addition to or subtraction from the set of explanatory variables based on some prespecified criterion. In this study, stepwise regression model was preferred among other regression models to compare with the performance of the GEP model derived.

EXPERIMENTAL PROGRAM

The primary focus of the experimental research on compressive strength of LWGM produced by LWFA and by product materials was to investigate the effectiveness of different quantities of binder, curing temperature and time. However, derivation of prediction models to skip time and effort consuming experimental stage. This provides a basis for the motivation of the current study.

In the preliminary study it was determined that utilization of lightweight fine aggregate (LWFA) by itself, had no problem of workability and consistency of the mix. Furthermore, the other challenges, for instance, separation of the large particles, demolding of the samples and comparatively lower compressive strength values obtained directed the authors to make a decision on beneficiation of crushed lime stone sand together with LWFA in the LWGM mixtures.

Materials

Since LWFA is decided to be used for production of LWGM, the fraction of the total aggregate volume for LWFA was taken as 70%, while 30% was considered for limestone aggregate. The grading of LWFA is coarser than crushed limestone aggregate. The details on physical and grading properties of the aggregates can be foun in [32].

The LWFA were immersed in water to obtain 100% saturation before mixing with the other ingredients. The excessive moisture on the surface of the aggregates was dried to get saturated surface dry condition. The result of the experimental study on the water absorption capacity of LWFA was shown in Table 1. It was observed that maximum saturation level is 26.6%.

For the production of geopolymer binders, two pozzolanic materials, namely FA and GGBFS, were activated by alkalis. ASTM C618 F class FA was obtained from Ceyhan Sugozu thermal power plant. In addition, GGBFS meeting the eligibility criteria specified in ASTM C 989 was used. As the alkaline activator mixture of Na_2SiO_3 and a 12 M NaOH solution in proportions of 1: 2.5 was used. The ratio of the alkali solution to the binder is equal to 0.50. The composition of the sodium silicate solution was selected to provide the optimal activation. The optimal activation is stated to be the highest geopolymerization level [32]. Accordingly, sodium silicate solution contains 29.4% SiO_2, 14.7% Na_2O and 55.99% water. The polycarboxylic ether based plasticizer was used to provide a consistent workability to the LWGM mortar and was taken as 5% of the binder.

Table 1. Water absorption for lightweight aggregate

Soaked in water (hour)	0.5	1	2	6	24	48	72
Water absorption %	20.689	21.275	22.463	24.113	26.628	26.719	26.81

Mix design

In the experimental program, mix proportion with the different amounts of ingredients, the effect of six levels curing time and four ranges curing temperature on the compressive strength of LWGM mortar were considered. The amounts of alkaline activator solution and the ratio of sodium silicate to sodium hydroxide solution was constant.The mixture proportions of mortars are presented in the previous study conducted by the authors [32]. All the mixtures of LWGMs were designed with alkaline solution only as the liquid component in the mixture. No additional water, Therefore to improve the workability and to make LWGM mix as a homogeneous mix an super plasticizer with specific gravity of 1.07 is added to the mix.

Mixing, Casting, and Curing regime

After preparing the alkaline liquids, a predetermined mixing procedure was applied as described in the previous study [32]. The fresh LWGM was poured in two layers in the moulds (50 x 50 x 50 mm). To provide the fresh with a proper compaction, a laboratory type vibrating table was used. The specimens were wrapped with heat resistant thin plastic film as shown in Fig. 2 to avoid evaporation of water.

Next, all the mixtures of FA and GGBFS based LWGM were placed in an oven under curing temperatures of 60, 80, 100 and 120 °C for accelerated curing periods of 2, 6, 8, 24, 48 and 72 h. Fig. 2 shows the specimens curing in the oven. Then specimens were demolded after the curing process and the specimens were tested.

Figure 2. Mortar curing.

EXPERIMENTAL TEST RESULTS

In this section, the data from the experimental work conducted in the previous work [32] are used to introduce modeling formulas for the compressive strength of geopolymer mortar (Table 2). Two methods are used to generate these formulas. The first is the simplified linear step-wise regression, while the second method is the genetic expression programming.

The compressive strength value was used as dependent variable, while curing time, temperature, and binder content are used as predictors.

Table 2. Compressive strength values of LWGMs with different binder amounts, curing time and curing temperature.

Mix ID.	Accelerated curing temperature(C°)	Time(h)	Compressive strength for different binder content (MPa)						
			650	750	850	950	1050	1150	1250
GGBFS based LWGM	60	2	6.89	8.56	9.12	10.68	8.45	10.8	12.55
		6	18.45	21.33	24.5	22.75	24.3	27.53	28.45
		8	19.8	23.39	26.14	28.05	29.6	28.92	29.44
		24	26.02	28.13	29.12	31.08	31.83	32.91	34.1
		48	27.5	30.76	32.07	33.98	32.6	35.98	38.01
		72	29.4	31.4	31.67	32.71	33.82	35.4	36.49
	80	2	11.16	12	12.63	11.08	16.73	11.35	16.37
		6	20.28	23.7	21.27	24.34	27.93	26.93	30.16
		8	23.28	24.74	27	27.33	29.4	28.25	31.12
		24	27.81	28.41	30.16	29.52	31.83	32.91	32.71
		48	29.8	29.3	31	30.88	32.27	34.1	35.54
		72	31.47	30.88	30.32	30.2	33.42	35.26	36.06
	100	2	14.74	20.92	22	22.51	25.62	26.39	23.89
		6	21.51	26.29	27	29.96	27.97	29.4	27.86
		8	23.39	27.21	29	30.04	29.32	29.72	29.96
		24	24	29.36	30	30.72	30.35	31.27	30.6
		48	26.1	29.79	30.6	31	30.9	31.95	32.51
		72	26.69	30.08	30.1	31.04	31.4	32.83	29.64
	120	2	18.37	21.39	23.19	22.47	27.16	27.37	28.25
		6	20.22	23.71	25.42	25.34	27.73	27.77	27.85
		8	21	24	26.73	24.82	26.93	27.49	28.61
		24	22.5	24.47	27	25	27.33	28	28.8
		48	22.71	24.62	27.49	26.57	28	28.5	31.2
		72	21.2	23.98	26.97	24.94	30.32	29.46	28.65
FA based LWGM	60	2	0	0	0	0	0	0	0
		6	4.7	4.42	4.74	5.62	5.26	5.78	6.81
		8	4.86	5.38	5.86	6.14	5.9	8.25	9.2
		24	9.44	10.32	12.71	13.78	14.38	18.45	18.13
		48	13.47	14.5	15.66	18.69	18.88	21.12	22.35
		72	14.1	15.3	17.97	19.68	21.71	23.51	25.78
	80	2	4.62	4.06	4.02	4.5	4.14	4.74	4.82
		6	5.97	6.61	9.12	10.44	13.03	13.85	14.6
		8	6.5	8.37	9.48	12.15	14.14	14.4	15.6
		24	11.28	14.7	15.34	17.21	19.28	19.5	21.64
		48	17.68	18	18.5	20.32	21	22.1	23
		72	18.08	19	21.56	22.76	22.8	24.3	24.72
	100	2	4.58	5.5	5.14	5.46	5.98	7.85	10.92
		6	8.05	9.4	13.07	13.75	14.86	17.37	17.5
		8	9.32	10.2	14.5	14.65	15.18	18.53	18.9
		24	11.6	14.1	16.02	18	18.97	19.84	21.43
		48	13.75	15.58	18.84	23.43	22.11	24.22	24.54
		72	17.29	18.65	22.47	23.94	23.15	25.34	25.46
	120	2	4.69	5.46	6.49	7.41	8.41	11	13.86
		6	9.82	11.12	12.43	13.82	14.06	16.77	18.05
		8	11.45	12	14.02	14.86	17.53	17.93	20.32
		24	15	17.8	18.76	20	22.43	23.9	23.71
		48	15.15	18.29	20.72	19.08	20.52	23.55	24.94
		72	16.5	18.9	21.12	19.84	21.31	21.91	23.9

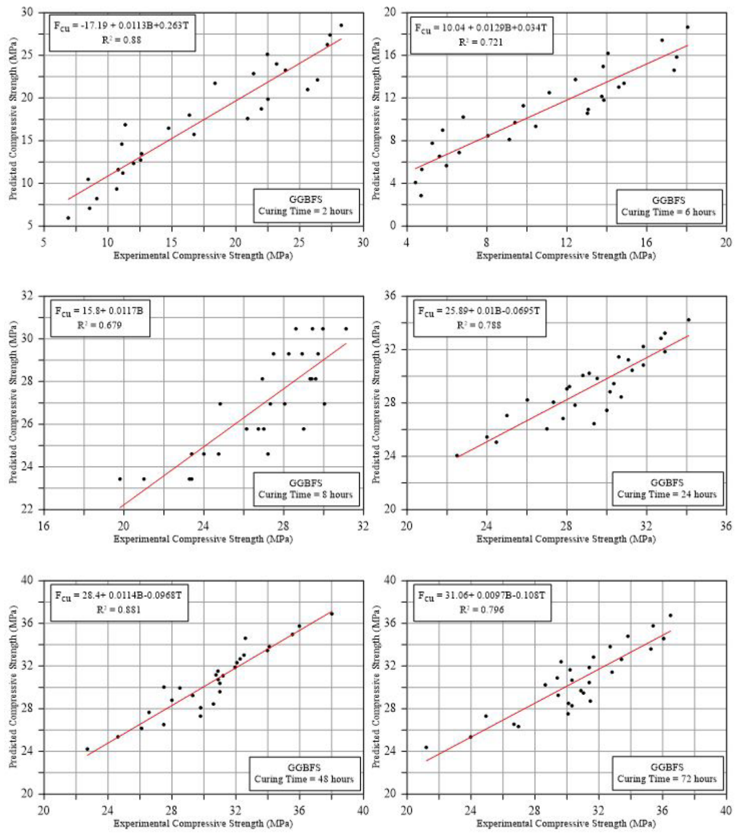

Figure 3. Step-wise formula of compressive strength versus GGBFS binder content and curing temperature for different curing times

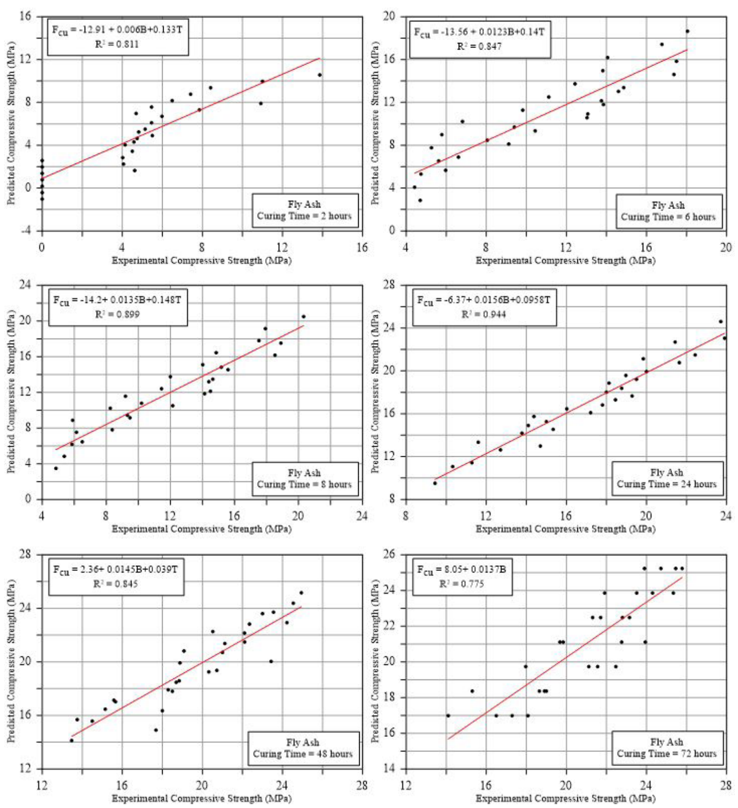

Figure 4. Step-wise formula of compressive strength versus fly ash binder content and curing temperature for curing time of 72 hours

STEP-WISE REGRESSION BASED COMPRESSIVE STRENGTH MODELING OF LWGM

Step-Wise Regression Relationships of Compressive Strength vs. Binder and Temperature for Various Curing Periods

In this section, the strength is correlated with both of the amount of binder and the curing temperature for different curing periods. Fig. 3 shows the conducted linear step-wise regressions for curing periods of 2, 6, 8, 24, 48, and 72 hours for both GGBFS and fly ash binders.

Fig. 3 shows the correlations of the strength values obtained from GGBFS based LWGM with the curing temperature and the binder content for different curing periods. In the formulas shown in Fig. 3, the binder contents vary from 650 kg/m^3 to 1250 kg/m^3, with steps of 100 kg/m^3. On the other hand, the included curing temperatures were 60, 80, 100, and 120 ^{o}C. As shown in the figure, although the regression is linear, the determination coefficients (R2) were good for all curing periods. The determination coefficients (R^2) for curing periods of 2, 6, 8, 24, 48, and 72 hours were approximately 0.88, 0.72, 0.68, 0.79, 0.88, and 0.8, respectively.

The correlations between compressive strength of fly ash-based geopolymer and both of binder (fly ash) content and the curing temperature are shown in Fig. 4 for curing periods of 2, 6, 8, 24, 48, and 72 hours. It is clear that these relations have better determination coefficients than those of GGBFS-based geopolymer. The determination coefficients for curing periods of 2, 6, 8, 24, 48, and 72 hours range from approximately 0.78 to approximately 0.94, while those of GGBFS were in the range of 0.68 to 0.88.

Step-Wise Regression Relationships of Compressive Strength Vs. Binder and Curing Time for Various Curing Temperatures

In this section, for each temperature, the strength of LWGM is correlated to binder content and curing period for different curing temperatures. The curing temperatures are 60, 80, 100, and 120 ^{o}C. Similar to the previous section, all formulas were found based on the binder content. The regression equations for GGBFS-based geopolymer are shown in Fig. 5, while Fig. 6 shows the regression equations of fly ash-based geopolymer.

It is clearly obvious that the degree of confidence of this set of equations is much lower than of that for different curing periods. In the equations predicted for different curing temperatures the coefficients of determination are mostly lower than 0.6, while for those of different curing periods, the lowest R2 is 0.66. The values of R^2 for compressive strength of GGBFS-based geopolymer for curing temperatures of 60, 80, 100, and 120 ^{o}C are approximately 0.56, 0.54, 0.53 and 0.79, respectively, as shown in Fig. 5.

As it is clear in Fig. 6, the determination coefficients of the compressive strength of fly ash-based geopolymer for different curing temperatures are better than their corresponding values with GGBFS binder. The coefficients of determination of compressive strength versus binder content and curing time for curing temperatures of 60, 80, 100, and 120 ^{o}C are approximately 0.83, 0.81, 0.8, and 0.69, respectively.

Step-Wise Regression Relationships of Compressive Strength vs. Binder, Curing Temperature, and Curing Time

In the previous sections, regression equations for compressive strength of geopolymer concrete based on only

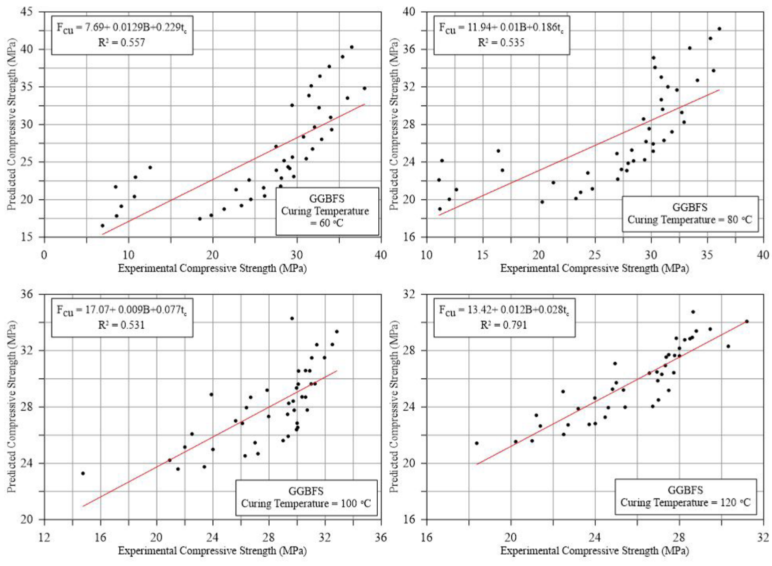

Figure 5. Step-wise formula of compressive strength versus GGBFS binder content and curing time for curing temperature of 120 ^{o}C

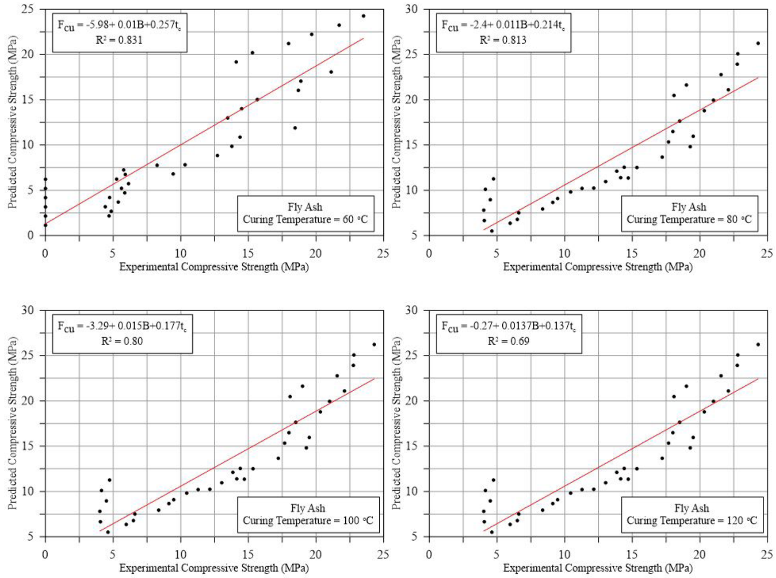

Figure 6. Step-wise regression formula for compressive strength versus fly ash binder content and curing time for curing temperature of 100 °C

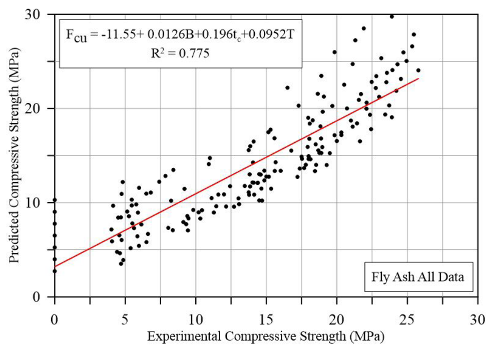

Figure 7. Step-wise regression formula for compressive strength versus fly ash binder content, curing temperature, and curing time

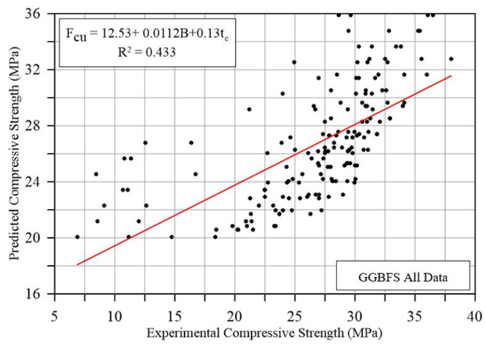

Figure 8. Step-wise regression formula for compressive strength versus GGBFS binder content, curing temperature, and curing time

two independent variables were obtained using linear step-wise regression. In this section, the compressive strength is correlated with the three independent variables at once. Thus, compressive strength is correlated to binder content, curing temperature, and curing time. Fig. 7 shows the experimental versus predicted compressive strength values for all experimental data of the FA based LWGMs. The coefficient of determination of this equation is approximately 0.78, which is quite good. Contrarily, for the GGBFS-based geopolymer concrete, the step-wise regression showed that curing temperature was insignificant with probability value greater than 0.05. Therefore, the equation was in terms of binder content and curing time only. However, the R^2 was as low as 0.43 (Fig. 8). In order to make a broad comparison of the prediction performance all of the derived step-wise regression formulas are presented in Table 3.

Table 3. Comparison of step-wise regression formulations.

Mix ID	*Definition*	*Step-wise regression formulas*	*R²*
GGBFS based LWGMs	Curing time = 2 hrs.	F_{cu}=17.19+0.0113B+0.263T	0.88
	Curing time = 6 hrs.	F_{cu}=10.04+0.0129B+0.034T	0.721
	Curing time = 8 hrs.	F_{cu}=15.8+0.0117B	0.679
	Curing time = 24 hrs.	F_{cu}=25.89+0.01B+0.0695T	0.788
	Curing time = 48 hrs.	F_{cu}=28.4+0.0114B+0.0968T	0.881
	Curing time = 72 hrs.	F_{cu}=31.06+0.0097B+0.108T	0.796
	Curing temperature=60 °C	F_{cu}=7.69+0.0129B+0.229 t_c	0557
	Curing temperature=80 °C	F_{cu}=11.94+0.01B+0.186 t_c	0.535
	Curing temperature=100 °C	F_{cu}=17.07+0.009B+0.077 t_c	0.531
	Curing temperature=120 °C	F_{cu}=13.42+0.012B+0.28 t_c	0.791
	All data	F_{cu}=12.53+0.0112B+0.13 t_c	0.433
FA based LWGMs	Curing time = 2 hrs.	F_{cu}= -12.91+0.006B+0.133T	0.811
	Curing time = 6 hrs.	F_{cu}= -13.56+0.0123B+0.14T	0.847
	Curing time = 8 hrs.	F_{cu}= -14.2+0.0135B+0.148T	0.899
	Curing time = 24 hrs.	F_{cu}= - 6.37+0.0156B+0.0958T	0.944
	Curing time = 48 hrs.	F_{cu}= 2.36+0.0145B+0.039T	0.845
	Curing time = 72 hrs.	F_{cu}= 8.05+0.0137B	0.775
	Curing temperature=60 °C	F_{cu}= -5.98+0.01B+0.25 t_c	0.831
	Curing temperature=80 °C	F_{cu}= -2.4+0.011B+0.214 t_c	0.813
	Curing temperature=100 °C	F_{cu} = -3.29+0.015B+0.177 t_c	0.80
	Curing temperature=120 °C	F_{cu}= - 0.27+0.0137B+0.137 t_c	0.69
	All data	F_{cu}= - 11.55+0.0126B+0.196 t_c +0.0952T	0.775

GENE EXPRESSION PROGRAMMING BASED COMPRESSIVE STRENGTH MODELING OF LWGM

In this section, the Gene Expression Programming (GEP) is used to evaluate the effects of the studied three parameters (binder content, curing temperature, and curing time) on compressive strength of LWGM. As in the previous section, the evaluation is in the form of a regression formula based on the type of binder. Thus, two formulas are to be conducted in this section, one for the FA based geopolymer, while the other is for GGBFS-based LWGM.

Although two third of the data were used as training and the rest were taken as testing data sets, for analysis of the results, all of them were considered to be a single cluster.

Gene expression programming (GEP), invented by Candida Ferreira [33], uses softwares by statments of the acquired models or presented knowledge [34]. Genetic programming, introduced by Koza [35], is a application of GAs [36]. Solving defined problem by employing a computer program is a commonly used solution. The definition of the problem is the first step in the logic of GP and GAs, and then the program runs to work out the problem in a problem-independent mode [36]. GEP is derived as an enhanced form of aforementioned genetic operators. These three algorithms use almost same genetic operators in the solutions with unimportant differences. Ferreira [33] states that the differences between the three algortihms denoted as "in GAs the individuals are linear strings of fixed length (chromosomes); in GP the individuals are nonlinear entities of different sizes and shapes (parse trees); and in GEP the individuals are encoded as linear strings of fixed length (the genome or chromosomes) which are afterwards expressed as nonlinear entities of different sizes and shapes (i.e., expression trees (ETs) or simple diagram representations)".

In this section, the GEP is used for formulation-based modeling of the compressive strength of the LWGM based on the experimental results of this study. This formulation is carried out based on the binder type, while binder content, curing temperature, and curing period are kept variables. Thus, two formulas are obtained using GEP. The first is for the compressive strength of fly ash-based LWGM, while the second is for the GGBFS-based LWGM. In both of which, the compressive strength is nonlinearly evaluated based on the binder content, the curing temperature, and the curing period as expressed in Equation 1. The total number of compressive strength results used in GEP for each binder was 168. The fitness function used in the GEP in this study is the coefficient of determination (R^2), which was also used in the step-wise regression in this study. The software named GeneXproTools.5.0 was benefited for derivation of the model, while Minitab 17 was used as statistical software for stepwise regression modelling.

$$F_{cu} = f(B, T, t_c) \tag{1}$$

In the GEP carried out in this study, thirty chromosomes each of 3 genes and head length of 7 were used, while the addition was used as the linking function to link the resulted expression trees. Thus, each resulted equation will be composed of three expression trees linked by addition. To simplify the resulted functions, only a limited set of mathematical operations were selected. These are square root, cubic root, squaring, cubing, natural logarithm, exponential, sin, and cosine as well as basic mathematical operations.

Fig. 9 shows the resulted expression trees of the strength of FA based samples, while Fig. 10 shows the expression trees of that of GGBFS samples. In these figures and the following equations, the parameters d_o, d_1, d_2 refer to the variables of the equation, which are the binder content (B), the curing temperature (T), and the curing time (t_c), respectively, while C_o and C_1 are constants of each sub-equation.

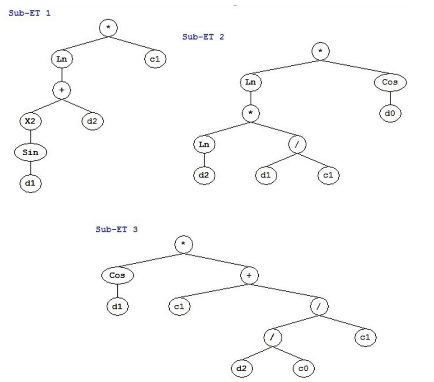

Figure 9. Resulted expression trees of compressive strength of fly ash-based geopolymer samples.

Equation 2 is the GEP prediction formula for the fly ash-based mortar, while Equation 3 is the prediction formula of compressive strength of the GGBFS based mortar.

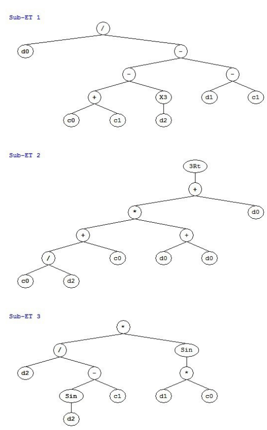

Figure 10. Resulted expression trees of compressive strength of GGBFS-based geopolymer samples.

Equations 2 and 3 are obtained from the expression trees illustrated in Figs. 9 and 10.

The obtained prediction values versus experimental ones are graphically demonstrated in Fig. 11 and Fig. 12 for FA based and GGBFS based LWGMs, respectively.

$$F_{cu} = F_1 + F_2 + F_3 \quad (2)$$

$$F_1 = c_1 ln\left[(\sin d_1)^2 + d_2\right] \quad (2a)$$

Where C_o = 4.00769 and C_1 = 4.87732

$$F_2 = \cos d_o ln\left[\frac{d_1}{C_1} lnd_2\right] \quad (2b)$$

Where c_o = -5.881989 and c_1 = 6.77649

$$F_3 = \cos d_1\left[c_1 + \frac{d_2 / C_o}{C_1}\right] \quad (2c)$$

Where c_o = -4.005798 and c_1 = 4.376678

Where F_1, F_2, and F_3 are the sub-function resulted from each sub-expression trees shown in Fig. 9, respectively, and connected by the addition linking function.
Equation 2 yielded a coefficient of determination of (R^2)0.95. as shown in Fig. 11, which is much better than that of stepwise regression, which was 0.775. This reveals the power of GEP compared to regression formulas. However, Equation 3 had a coefficient of determination of 0.866. Although it is slightly less than the former, it is even so better than that of the prediction model expressed by linear step-wise regression (0.433). This assures that GEP is much powerful than traditional statistical regression tools.

$$F_{cu} = F_1 + F_2 + F_3 \quad (3)$$

Where F_1, F_2 and F_3 are given by Equations (7), (8), and (9), respectively.

$$F_1 = d_o / \left[\left(c_o + c_1 - d_2^3\right) - \left(d_1 - c_1\right)\right] \quad (3a)$$

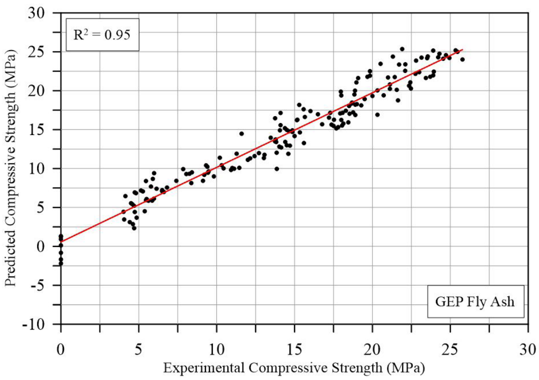

Figure 11. GEP prediction vs experimental compressive strength of FA-based-LWGM (168 specimens)

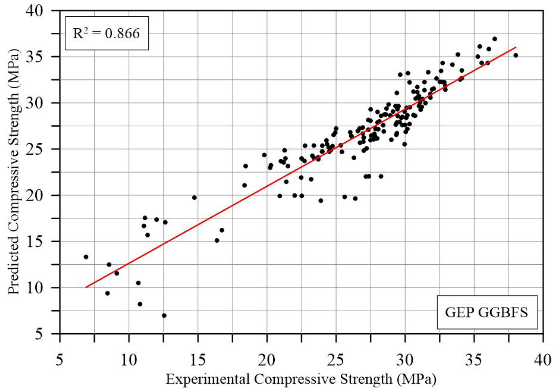

Figure 12. GEP predicted vs experimental compressive strength of GGBFS-based-LWGM compressive strength of 168 specimens.

Where c_o = 7.316192 and c_1 = 7.221954

$$F_2 = \sqrt[3]{2d_o\left(c_o + \frac{C_o}{d_2}\right) + d_o} \quad (3b)$$

Where c_o = 9.992737 and c_1 = -5.524353

$$F_3 = \left[d_2 / \left(\sin d_2 - C_1\right)\right] \sin C_o d_1 \quad (3c)$$

Where c_o = 7.880677 and c_1 = -9.897583

CONCLUSION

The GEP prediction formulas for the fly ash and GGBFS-based lightweight LWGM were compared to those obtained from stepwise regression. The GEP equation for FA based LWGM has a coefficient of determination of R^2 = 0.95 which is much better than that of stepwise regression, which was 0.775. This reveals the power of GEP to predict regression formulas. The analyses have also indicated that GEP prediction compressive strength values for GGBFS-based LWGM were quite closer to the experimental ones than traditional statistical regression tools.

For future studies other powerful soft computing techniques may be utilized for derivation of estimation models for such construction materials. These tools are artificial neural networks, artificial neuro fuzzy inference systems, fuzzy logic etc. However, the GEP model exploits the input data as they are i.e. without needing preprocessing before they are introduced to the software. Therefore, this method may be considered as a more user friendly technique than the other modeling methods. However, when the accuracy of the prediction values are taken into account, then the utilization of the sophisticated techniques become more prominent. In such cases, the possible solution offered may be the computerization of the complicated models through special softwares. In such a way, the disadvantage due to the complexity of the estimation models can be eliminated.

REFERENCES

1. Davidovits J. Global Warming Impact on the Cement and Aggregate Industry. World Resource review 6(2) (1995) 263-278.
2. Turner LK, Collins FG. Carbon dioxide equivalent (CO2-e) emissions: A comparison between geopolymer and OPC cement concrete. Construction and Building Materials 43 (2013) 125-130.
3. Cristelo N, Tavares P, Lucas E, Miranda T, Oliveira D. Quantitative and qualitative assessment of the amorphous phase of a Class F fly ash dissolved during alkali activation reactions – Effect of mechanical activation, solution concentration and temperature. Compos Part B Eng. 103 (2016) 1-14.
4. Zivica V, Palou MT. Physico-chemical characterization of thermally treated bentonite. Compos Part B Eng. 68 (2015) 436-445.
5. Masi G, Rickard WDA, Bignozzi MC, van Riessen A. The effect of organic and inorganic fibres on the mechanical and thermal properties of aluminate activated geopolymers. Compos Part B Eng. 76 (2015) 218-228.
6. Kheradmand M, Mastali M, Abdollahnejad Z, Pacheco-Torgal F. Experimental and numerical investigations on the flexural performance of geopolymers reinforced with short hybrid polymeric fibres. Compos Part B Eng 126 (2017) 108-118.
7. Roviello G, Menna C, Tarallo O, Ricciotti L, Messina F, Ferone C, Asprone D, Cioffi R. Lightweight geopolymer-based hybrid materials. Compos Part B Eng. 128 (2017) 225- 237.
8. Nematollahi B, Sanjayan J, Shaikh FUA. Matrix design of strain hardening fiberr reinforced engineered geopolymer composite. Compos Part B Eng. 89 (2016) 253-265.
9. Yan S, He P, Jia D, Wang J, Duan X, Yang Z, Wang S, Zhou Y. Effects of high temperature heat treatment on the microstructure and mechanical performance of hybrid Cf- SiCf-(Al2O3p) reinforced geopolymer composites. Compos Part B Eng. 114 (2017) 289-298.
10. Pacheco-Torgal F, Labrincha JA, Leonelli C, Palomo A, Chindaprasirt P. Handbook of alkali-activated cements, mortars and concretes, Woodhead Publishing, Cambridge, 2015.
11. Aydın S, Baradan B. Effect of activator type and content on properties of alkali activated slag mortars. Compos Part B Eng. 57 (2014) 166-172.
12. Kürklü G. The effect of high temperature on the design of blast furnace slag and coarse fly ash-based geopolymer mortar. Compos Part B Eng. 92 (2016) 9-18.
13. Aydın S, Baradan B. The effect of fiber properties on high performance alkali-activated slag/silica fume mortars. Compos Part B Eng. 45(1) (2013) 63-69.
14. Glukhovsky VD, Rostovskaja GS, Rumyna GV. High strength slag-alkaline cements, 7th International Congress on the Chemistry of Cements, Paris, pp. 164-168, 1980.
15. Kutti T, Malinowski R, Srebrenik M. Investigation of mechanical properties and structure of alkali activated blast furnace slag mortars. Silicates Industriels 6 (1982) 149-158.
16. Fernandez-Jimenez A, Puertas F, Arteaga A. Determination of kinetic equations of alkaline activation of blast furnace slag by means of calorimetric data. J. Therm. Anal. Calorim. 52 (1998) 945-955.
17. Balçıkanlı M, Özbay E. Optimum design of alkali activated slag concretes for the low oxygen/chloride ion permeability and thermal conductivity. Compos Part B Eng. 91 (2016) 243-256.
18. Yip CK, Lukey GC, van Deventer JSJ. The coexistence of geopolymeric gel and calcium silicate hydrate at the early stage of alkaline activation. Cem. Concr. Res. 35(9) (2005) 1688–97.
19. Yip C, van Deventer J. Microanalysis of calcium silicate hydrate gel formed within a geopolymeric binder. J. Mater. Sci. 38(18) (2003) 3851–60.
20. Juenger MCG, Winnefeld F, Provis JL, Ideker JH. Advances in alternative cementitious binders, Cem. Concr. Res. 41(12) (2011)1232–43.
21. Lloyd N, Rangan B. Geopolymer concrete with fly ash. In: Second international conference on sustainable. Const, Mater. and Tech. (2010) 1493–504.
22. Komnitsas K, Zaharaki D. Geopolymerization: a review and prospects for the minerals industry, Miner. Eng. 20(14) (2007) 1261–77.
23. Tempest B, Sanusi O, Gergely J, Ogunro V, Weggel D. Compressive strength and embodied energy optimization of fly ash based geopolymer concrete, In: Proceedings of the 2009 world of coal ash (WOCA) conference Lexington, KY, USA, 2009.
24. Singh PS, Trigg M, Burgar I, Bastow T. Geopolymer formation processes at room temperature studied by 29Si and 27Al MAS-NMR, Mater. Sci. Eng. 396(1– 2) (2005) 392–402.
25. Kumar S, Kumar R, Mehrotra SP. Influence of granulated blast furnace slag on the reaction, structure and properties of fly ash based geopolymer J. Mater. Sci. 45 (3) (2010) 607–615.
26. Rashad AM. Properties of alkali-activated fly ash concrete blended with slag, Iran. J. Mater. Sci. Eng. 10 (1) (2013) 57–64.
27. Ismail I, Bernal SA, Provis JL, San Nicolas R, Hamdan S, van Deventer JS. Modification of phase evolution in alkali-activated blast furnace slag by the incorporation of fly ash. Cem. Concr. Compos. 45 (2014) 125–135.
28. Garcia-Lodeiro I, Fernández-Jiménez A, Palomo A. Hydration kinetics in hybrid binders: early reaction stages, Cement Concr. Compos. 39 (2013) 82– 92.
29. van Jaarsveld J, van Deventer J. The effect of metal contaminants on the formation and properties of waste-based geopolymers. Cem. and Concr. Res. 29(8) (1999) 1189-1200.
30. Ismail I, Bernal SA, Provis J, San Nicolas R, Brice DG, Kilcullen AR, van Deventer JS. Influence of fly ash on the water and chloride permeability of alkali activated slag mortars and concretes. Constr. Build. Mater. 48 (2013) 1187– 1201.
31. Parthiban K, Saravanarajamohan K, Shobana S, Bhaskar AA. Effect of replacement of slag on the mechanical properties of fly ash based geopolymer concrete, Int. J. Eng. Technol. 5 (3) 2555–2559, 2013
32. Mermerdaş K, Algın Z, Oleiwi SM, Nassani DE. Optimization of lightweight GGBFS and FA geopolymer mortars by response surface method, Construction and Building Materials 139 (2017), 159-171.
33. Ferreira C. Gene expression programming; a new adaptive algorithm for solving problems. Complex Syst 12(2) (2001) 87-129.
34. Li X, Zhou C, Xiao W, Nelson PC. Prefix gene expression programming. in Late Breaking Paper at the Genetic and Evolutionary Computation Conference (GECCO), Washington, D.C., 2005.
35. Koza JR. Genetic programming; on the programming of computers by means of natural selection, MIT Press, USA, 1992.
36. Gen M, Cheng R. Genetic algorithms and engineering design, Wiley, USA, 1997.