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Prediction Of Strength Properties Of Geopolymer Concrete Using Artificial Intelligence Techniques

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Abstract

Several studies have successfully used fly-ash (FA)-like waste material for the manufacturing of geopolymer concrete (GPC). This study uses gene expression programming (GEP), a type of soft computing approach, to produce an empirical equation that estimates the compressive strength fc0 of GPC using FA. Through a thorough analysis of the published research, a consistent, large, and trustworthy data set is assembled in order to develop a model. 298 fc0 experimental outcomes make up the collected data set. The following are considered explanatory variables: the amount of extra water added as percent FA (%EW), the percentage of plasticizer (%P), the initial curing temperature (T), the specimen's age (A), the curing duration (t), the ratio of fine aggregate to total aggregate (F/AG), the percentage of total aggregate by volume (%AG), the molarity of the NaOH solution, the activator or alkali to FA ratio (AL/FA), the ratio of sodium oxide (Na2O) to water (N/W) for preparing Na2SiO3 solution, and the ratio of Na2SiO3 to NaOH (Ns/No). An empirical GEP equation is put forth to calculate the fc0 of GPC using FA. The suggested model's precision, applicability, and forecasting capacity were assessed using parametric analysis, statistical verification, and a comparison with both linear and non-linear regression equations.

Keywords: artificial intelligence; gene expression programming; fly ash; waste materials; geopolymer; regression analysis; building materials; sustainable construction materials; smart cities; sustainable concrete; cement

1. Introduction

The unburned residual waste from thermal coal plants is known as fly ash (FA) [1]. This is carried by gases released by the boiler's combustion zone. FA is gathered using an electrostatic or mechanical separator [2]. Globally, 375 million tonnes of FA are produced annually, and the cost of disposal might reach $20–40 per tonne [3]. In suburban regions, it is disposed of in landfills [4]. On the other hand, dumping tonnes of FA without treatment have a harmful effect on the environment [5]. The dangerous components of FA, including as alumina, silica, and oxides like ferric oxide (Fe_2O_3), operate as mediators in the contamination of the air, water, and soil. In the end, this results in various geo-environmental difficulties and health concerns [6, 7]. Maintaining a safe environment over time requires effective waste management [8]. If FA is not disposed of appropriately, it will impact the entire ecological cycle. When ultra-fine FA particles enter the pulmonary system, they behave similarly to poison. Thus, leading to physiological imbalances and other associated medical conditions such as cancer, hepatic dysfunction, anaemia, dermatitis, and gastroenteritis. FA contaminates surface and subsurface water, endangering aquatic life and resulting in skin conditions and diarrhoea [7].
Concrete is the second most consumable material after water and is utilised in building all around the world [9, 10]. It is estimated that three tonnes of concrete are produced for every person. Globally, over 25 billion tonnes of concrete are produced annually. Global statistics for the current year indicate that about 2.6 billion tonnes of cement are produced annually. Over the following ten years, this will increase by 25%. Cement production, however, has a negative impact on the environment. To make one tonne of cement, one tonne of CO_2 is released into the atmosphere. This puts the environment in a worrying predicament. The primary ingredient in regular Portland cement is limestone. It's possible that severe limestone shortages may happen in 25–50 years. The global building sector is responsible for 30% of CO_2 emissions and uses one-third of all resources. Green concrete manufacturing is therefore crucial to minimising harmful environmental consequences. FA can be added to the cementitious matrix as an additional material. Researchers have used it to create green concrete. Using FA in the building sector is a wise decision since it will cut down on the amount of cement used and the negative effects of landfill disposal.
Since less cement is needed to make geopolymer concrete (GPC), the usage of this FA-like waste-derived geopolymer concrete has increased during the past 20 years. Although FA has been employed successfully in the construction sector, its application is still restricted because of its unusual behaviour. Builders use FA-dependent GPC widely. There isn't a way to calculate the mechanical characteristics of FA-based GPC using a mix ratio that has the most variations. The extra water added as percent FA (%EW), the percentage of plasticizer (%P), the initial curing temperature (T), the specimen's age (A), the length of the curing period (t), the fine aggregate to total aggregate ratio (F/AG), the percentage of total aggregate by volume (%AG), the molarity of the NaOH solution, the activator or alkali to FA ratio (AL/FA), the sodium oxide (Na_2O) to water ratio (N/W) for preparing Na2SiO3 solution, and the Na_2SiO_3 to NaOH ratio (Ns/No) are some of the parameters that have a critical impact on the mechanical properties of FA-based GPC. This gives the GPC's prediction properties some uncertainty. Furthermore, there has been a noticeable upsurge in the use of soft computing methods for developing empirical models in recent times. One of the widely used soft computing techniques, gene expression programming (GEP) is applied by several researchers from a variety of engineering viewpoints. The gene-level replication of DNA molecules serves as the model for actual GEP. Different mechanical characteristics of lightweight concrete exposed to high temperatures were anticipated by Tanyildizi et al. With chromosomal levels equal to 30, head size of 8, and number of genes equal to 4, the author predicted two distinct GEP models. The two distinct linking functions that are employed are addition and multiplication. The population size is determined by the chromosomal level, which also affects the GEP execution time. Chromosome genetic variation is aided by genetic operators. Up until an acceptable fitness is reached, the chromosome that produces the greatest outcomes is passed on to next generations, and the process is repeated. The GEP has been used recently by a variety of studies to estimate the mechanical properties of various concrete kinds. The researchers employ GEP to forecast the compressive strength of sugar cane bagasse ash (SCBA) concrete using experimental and literature-based data. Additionally, the authors suggested a formula with just 277 occurrences that uses GEP to estimate the axial capacity of concrete filled steel tubes (CFST). Additionally, Nour et al. estimated the compressive strength of CFST incorporating recycled aggregates using GEP methods.

2. Research Methodology

In this segment, methodology for the establishment of an empirical model for the compressive strength (f_c^0) of GPC made with FA has been incorporated.

2.1. Brief Review of Genetic Programming and Gene Expression Programming

To offer a different approach for fixed-length binary strings (used in GAs), Koza suggested the GP technique. The collection of terminals (constants and input variables), the set of primitive functions (domain-explicit functions), the fitness evaluation, the control variables (population size and cross-over, etc.), and the termination criteria followed by a result designation method are the five main parameters to be defined throughout the GP methodology. The versatility of GP programming approach stems from the introduction of non-linear parse tree-like structures. Based on the data, it presumes any starting non-linearity. There has been prior use of a non-linearity of a comparable sort. The ignorance of the independent genome is GP's limitation. Non-linear structures, which serve as the phenotype and genotype, are used in GP. It is hence unlikely to provide simple, straightforward phrases. Ferreira suggests the GEP approach as an adaptation of the GP method to address its shortcomings. The fact that just the genome is passed on to the next generation is a major change that occurs during GEP. The formation of entities by a single chromosome made up of different genes is another notable feature. Each gene in GEP is represented by fitting length parameters, terminal sets of constants, and arithmetic operations as the functions. Moreover, there is a stable relationship between the chromosomal symbol and the related function in genetic code operators. The chromosomes contain the information required to create an empirical model, and in order to deduce this information, a novel programme known as karva is created.
The process begins with the arbitrary creation of fixed-size chromosomes for every individual. These chromosomes are then transformed into expression trees (ET), and the fitness strength is calculated for every individual. The replication process for several creations continues with fresh participants until excellent outcomes are achieved. Population manipulation uses genetic processes including crossover, reproduction, and mutation.

2.2. Data Collection

The primary consideration in the study and design of concrete structures is compressive strength (f_c^0). The creation of an exact and trustworthy expression that can link the mix percentage and $f_c^0$of GPC manufactured with FA is necessary in order to save time, money, and to maintain the usage of FA in the construction sector.
A comprehensive database for FA-based GPC's $f_c^0$was assembled from previously published experimental studies. There are 298 samples altogether in the database, consisting of 31 cube specimens measuring 150 mm and 100 mm, height × diameter, 166, and 101 cylindrical specimens measuring 200 mm × 100 mm. f_c^0 of cylindrical and cube specimens is dependent on the L/D ratio (length to diameter). 100 mm cubes have a fc0 that is 5% higher than 150 mm cubes. However, the fc0 of 150 mm cubes is 20% higher than that of 100 mm × 200 mm cylindrical specimens. A specimen with a smaller dimension will have a lower fc0 than a specimen with a greater size because as the specimen's volume grows, so does the number of voids. Additionally, there exists an inverse relationship between the stress and the specimen's cross-sectional area. stronger stresses indicate a stronger internal resistance to failure in the case of the one with the smaller cross-sectional area.

Data about the explanatory parameters are covered by the composed database, which includes the percentage of plasticizer (%P), the amount of extra water added as percent FA (%EW), the specimen's age (A), the length of time it took to cure (t), the ratio of fine aggregate to total aggregate (F/AG), the percentage of aggregate by volume (%AG), the percentage of SiO_2 solids to water (% S/W) in a solution of sodium silicate (Na_2SiO_3), the molarity of the NaOH solution (M), the ratio of activator or alkali to FA (AL/FA), and the ratio of Na2SiO3 to NaOH (Ns/No) for the response of compressive strength. First, all of the samples that were gathered for the aforementioned criteria were heat cured for 24 hours at various temperatures. Researchers found that although the f_c^0 of FA-based GPC rises with curing time, the rate of increment is fast up to 24 hours. Because of the geopolymerization process, GPC has a greater early strength, and there isn't much research on extended curing times. According to Van Jaarsveld et al., the f_c^0 does not grow over a cure duration of more than 24 hours. All models' performances rely on how the explanatory parameters are distributed. More detail is provided to the data by the bar charts that have been put above and to the right of the main plot. It displays the compressive strength distribution in addition to the input variable distribution. Each explanatory variable has a significant effect on how the FA-based GPC's compressive strength varies.

Both cubes and cylindrical specimens are enumerated in order to create a database for the generalised investigation. It is recommended to use the recommended model with the given ranges in order to obtain accurate and consistent compressive strength estimates. It should be mentioned that several studies were carried out in order to assess the database's consistency, validity, and dependability. When creating and assessing the model, datasets that deviated significantly from the world average (20%) were excluded. 298 datasets for compressive strength prediction were utilised to create an empirical model. The training and validation sets are two statistically consistent sets of data points that were randomly separated from the rest of the data points in this study. Additionally, the training set receives 70% (208 data points) of the entire data, whereas the validation set receives 30% (90 data points). The training set was used to train the gene progression empirical model, while validation data sets were used to calibrate and justify the constructed model's capacity to generalise, as recommended by the literature.

3. Results and Discussion

The GEP algorithm's output for the compressive strength (f_c^0) model as an expression tree is shown in Figure 1.

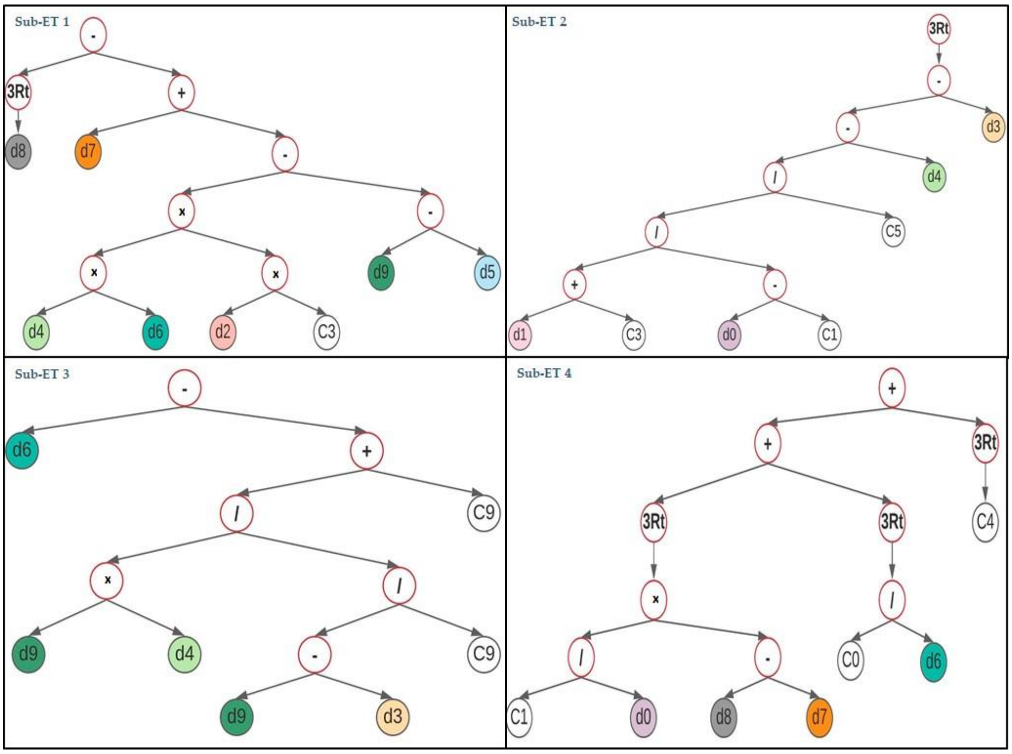

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Figure 1. GEP model expression trees (ETs) for compressive strength f_c .

GEP ETs use the indicators to express the explanatory variables. The corresponding symbols and description of each indicator are provided in Table 1.

Table 1. Indicators of GEP expression tree.

Indicator in Expression Tree	Description	Symbol
do	The temperature for curing in degrees Celsius	T
d1	The age of the sample	A
d2	Ratio of alkali or activator to the fly-ash	AL/FA
d3	Ratio of Na_2SiO_3 to NaOH	Ns/No
d4	NaOH solution molarity	M
d5	Percentage of total aggregate by volume	% A_G
d6	Ratio of fine aggregate to total aggregate	F/A_G
d7	Plasticizer as percent fly-ash	% P
d8	Percentage of SiO_2 solids to water ratio	%S/W
d9	Extra water addition as percent fly ash	% E_W

3.1. Sensitivity and Parametric Analysis

Figure 2 displays the sensitivity analysis results. The image makes clear that the explanatory parameters' participation in the fc0 of GPC manufactured with FA is identical whether seen through the lens of material engineering.

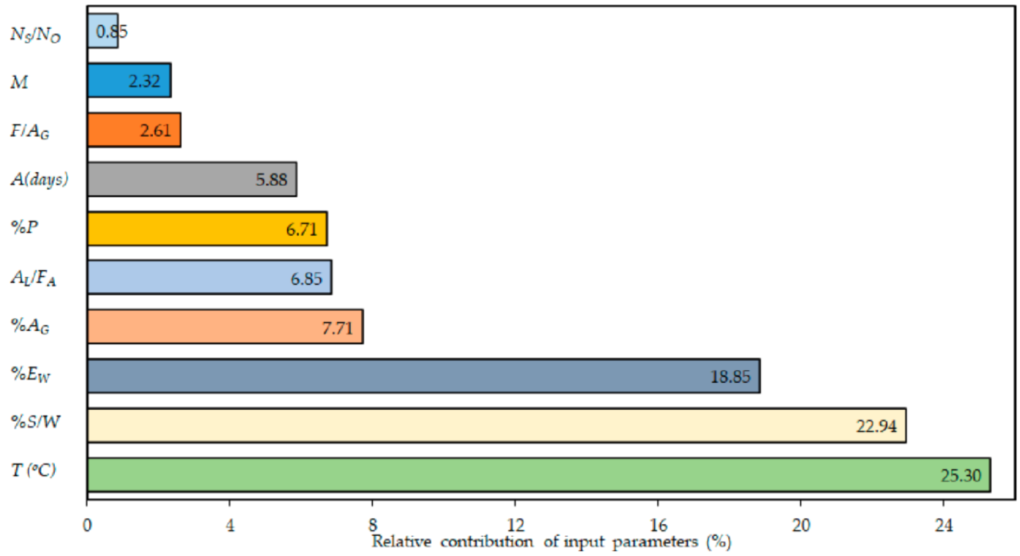

Figure 2. Percent relative contribution of input parameter.

Furthermore, parametric analysis is used to determine the most important input factors' efficacy in projecting the compressive strength of FA-dependent GPC. Only one variable's value was changed from maximum to lowest to record changes in compressive strength; all other inputs were kept at average levels.

3.2. Performance Evaluation of GEP Models

The previous study indicated that a minimum ratio of three should be reached between the number of data points in the database and the number of input parameters in order to produce a dependable GEP equation. However, a greater value of 30 has been employed in this investigation. The statistical analysis for the GEP model's training and validation sets is shown in Table 2. These findings show how well models can be trained and how well experimental and less error-prone projected outcomes correlate. The GEP model's training set's RMSE, MAE, and RSE are 5.971, 5.832, and 0.325, respectively. These values are derived from the validation samples as 2.643, 2.057, and 0.0675. The training and validation sets' statistical measures are comparable, indicating the model's greater capacity for generalisation. As a result, the created model is capable of making precise and trustworthy predictions for the new data. As ideal situations equal zero, Table 5 witnesses ρ approach zero.

Table 2. Statistical analysis of GEP, linear, and non-linear regression models.

	RMSE		**MAE**		**RSE**		**RRMSE (%)**			**R**		**ρ**
Model	**TR 1**	**VDN 2**	**TR**	**VDN**	**TR**	**VDN**	**TR**	**VDN**	**TR**	**VDN**	**TR**	**VDN**
GEP	5.971	2.643	5.823	2.057	0.325	0.0675	16.949	4.949	0.8586	0.9643	0.0911	0.02519
Linear	6.986	5.546	6.543	4.967	0.589	0.304	19.20	10.21	0.8074	0.8976	0.1062	0.05382
Non-Linear	6.593	5.054	6.053	4.875	0.497	0.298	18.53	9.021	0.8357	0.9247	0.1009	0.04687

[1] T_R symbolizes training sample; [2] V_{DN} symbolizes validation samples.

4. Conclusions

In this study, an expression for the estimate of the compressive strength, f^0, of fly-ash-based geopolymer concrete (GPC) is established using the gene expression programming approach (GEP). With its widely dispersed database of many parameters drawn from the published literature, the predicted GEP model is empirical in nature. Explanatory variables that are extremely important and noticeable are taken into account for the prediction of the f_c^0 of fly-ash-based GPC. The experimental results are satisfied by the projected model outcomes. It is evident from the parametric analysis that the projected model effectively takes into account the influence of the input parameters in order to forecast the precise pattern of fly-ash-based GPC. By analysing and evaluating the statistical tests MAE, RSE, R, and RMSE as well as fitness functions (ρ) for training and validation samples, the accuracy of the projected models is confirmed. In addition, the model accurately satisfies the necessary criteria taken into account for external validation. When the suggested model is compared to basic linear and non-linear equations, it becomes clear that the GEP model has greater predictive power and generality, making it suitable for use in the first fly-ash-based GPC design. Moreover, a leachate analysis is advised prior to using fly ash as a geopolymer binder. The anticipated models have the potential to offer a comprehensive and useful basis for using harmful fly ash in building processes rather than disposing of it in landfills. Because green concrete is manufactured by using discarded fly ash, which lowers energy consumption, greenhouse gas emissions, disposal expenses, and building costs, this would result in efficient and sustainable construction.

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