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Investigating the influence of sample age and cement blaine on compressive strength mortar and concrete: A predictive modeling approach using Gene Expression Programming

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ABSTRACT

This paper investigates the intricate relationship between sample age, cement blaine, and the compressive strength of mortar and concrete. Specifically, it focuses on understanding how these factors influence the mechanical properties of these materials at two critical time points: 7 and 28 days. Through a comprehensive analysis, this study sheds light on the evolving characteristics of mortar and concrete over time. To achieve this, we introduce a novel predictive modeling approach based on Gene Expression Programming (GEP). This innovative methodology allows us to anticipate variations in compressive strength accurately. By incorporating the effects of both sample age and cement blaine, our GEP-based model provides valuable insights into the mechanical behavior of mortar and concrete. The findings of our research reveal essential correlations between sample age, cement blaine, and compressive strength. These insights contribute significantly to a deeper understanding of the factors influencing the performance of concrete materials. Moreover, our proposed GEP-based model emerges as a robust tool for forecasting compressive strength, offering engineers and designers enhanced capabilities to optimize concrete mixtures and design structures with superior performance and durability. Overall, this study not only advances our understanding of the complex interplay between sample age, cement blaine, and compressive strength but also offers practical solutions for improving the design and performance of concrete structures in various applications.

KEYWORDS: Compressive strength; sample age; cement Blaine; Gene Expression Programming (GEP).

1 INTRODUCTION

Cement is regarded as a fundamental substance in cementitious materials, including cement mortar and concrete [1]. The presence of cement as an adhesive in compounds plays a crucial and indispensable role in the resistance properties of cementitious materials [2]. Many laboratory investigations have thus far focused on examining the impact of cement on the fresh and hardened properties [3], chemical properties [4], and microscopic structure of cement-based materials [5].

However, due to the high costs and potential human errors associated with laboratory programs involving the preparation and production of cementitious materials, researchers worldwide have turned their attention to the utilization of artificial intelligence techniques as a viable and efficient alternative [6]. In recent times, a variety of artificial intelligence methods, such as artificial neural networks [7], gene expression program [8], fuzzy logic [9], and support vector machines [10], have been employed to predict the properties and characteristics of cementitious materials.

Among the aforementioned methodologies, the Gene Expression Program methodology emerges as one of the most renowned and pragmatic approaches owing to its exceptional aptitude in classifying data and establishing correlations between input and output in order to tackle intricate predicaments [11]. These advantages encompass its suitability as a proficient soft computing technique for predicting various civil engineering problems, and its provision of an effective explicit formulation to facilitate the prediction process [12]. The GEP model has been employed to forecast the mechanical and physical properties of diverse types of cementation materials, which comprise mortar [13], OPC [14], HPC [15], LWC [16], etc [17].

Recently, there has been an increased reception towards the examination of the attributes of cement materials, namely cement mortar and concrete, through the utilization of the Gene Expression Program method. Azimipour et al [18] investigated on the influence of nano and micro silica, employing gene expression program methods, on the compressive strength of cement mortar. This was achieved through the examination of 480 sample designs, encompassing various ratios of water to cement and sand to cement, various percentages of NS and MS as well as the age of the samples. The results showed that age is one of the most influential input parameters in this modeling.

Based on the provided research background, thus far there has been a dearth of studies conducted about the concurrent impact of cement fineness and sample age on the compressive strength of mortar and concrete through the implementation of the Gene Expression Programming. Consequently, the objective of the predicting research endeavor is to construct a genetic model that takes into account the age of the samples and directs its focus towards the role of cement fineness on the proportion ratio of the compressive strength of cement mortar to concrete. To this end, the proposed model is predicated upon a thorough investigation involving 216 samples over the course of one year at the Zaveh Torbet cement company. The outcomes of this research serve as a foundation for the studies of other scholars and facilitate an enhanced comprehension of the significance of cement fineness and sample age in artificial intelligence models.

2. Materials, preparation of specimens, and curing

During one year of operation at the Zaveh Torbet cement factory, a total of 72 mixing designs were examined, with 216 samples being prepared and analyzed (each mixing design has three samples). To create these samples, the initial step involved preparing the mortar using a weight of sand to cement ratio is 2.75 and water to cement ratio is 0.485, following the guidelines outlined in the ASTM C305 standard [19] and for this purpose, fine aggregate with specific gravity of 2.6 and the fineness modulus of 2.48, as shown in Figure 1.

The process of creating the mortar began with the addition of water at a temperature of 20∓2℃, followed by the introduction of cement for a duration of 90 seconds at a low speed of approximately 60 rpm. Subsequently, the sand was added to this mix and the mixture was further agitated at a medium speed of around 75 rpm for 15 seconds. The mechanical mortar is combined and transferred into cube molds with measurements of 160×40×40 mm. Following a 24-hour period, the samples are extracted from the molds (Figure 2) and subjected to the water tank in accordance with ASTM C109 [20]. After curing for 7 and 28 days have elapsed since the samples were initially prepared for uniform loading, they are dried and any loose particles adhering to the loading surfaces are eliminated.

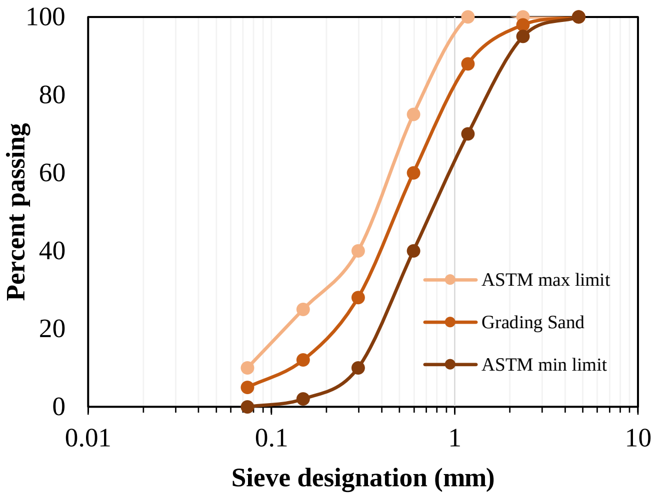


Figure 1. Particle size distribution of fine aggregate.

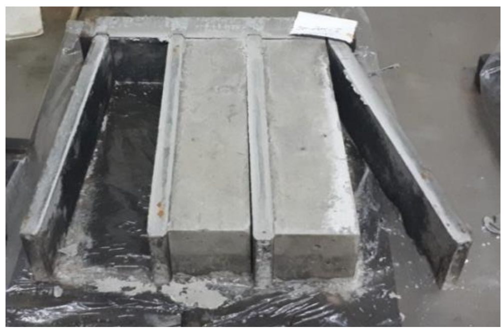


Figure 2. Cube molds for flexural strength of cement mortar.

3. GEP method and proposed model

Providing an appropriate model is a crucial requirement for laboratory research. By developing a suitable model for laboratory inputs that possesses the capability to accurately estimate the outputs, any desired input can be incorporated into the relationship and an appropriate estimation for the output can be obtained. It should be acknowledged, however, that due to factors such as testing errors and uncertainties, there will never be a direct relationship to precisely estimating laboratory results. Nonetheless, the outcome can always be predicted through interpolation or extrapolation using existing data. It is feasible to establish a relationship that contains an acceptable level of error. In recent years, various researchers have proposed different prediction methods, such as GEP or GA, which aim to provide relationships based on experimental data. Due to the unfamiliar composition of the accessible data, the formulated algorithms are employed in instances where a Gene expression program is utilized [21]. To ascertain the appropriate correlation relating to the compressive strength of cement mortar to concrete, a laboratory sample featuring diverse parameters such as cement fineness and sample age was employed in order to predict using the Gene Expression Programming approach. The technique employed by various researchers to establish relationships for structures is a variant of genetic programming that employs the manifestation of nonlinear chromosomes. The parameters employed in this methodology consist of links that encompass genes that are encoded via intricate computer programs. This distinctive approach possesses the capability to retain multiple solutions to a given problem within a singular chromosome. The aforementioned technique employs both crossover and mutation to sustain the ongoing process (Figure 3).

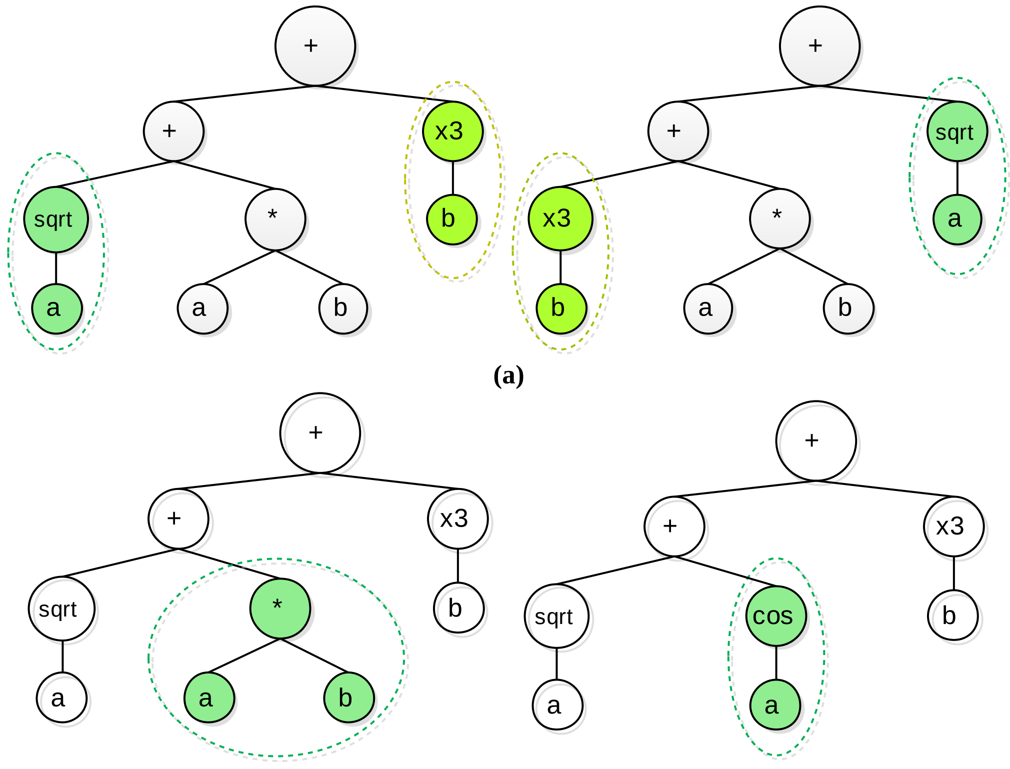


Figure 3. Tree representation of chromosome in GEP, (a) crossover, (b) Mutation [22].

By utilizing this methodology, the optimal solution, characterized by the minimum error rate and the greatest compatibility with the experimental findings, can be selected. In order to establish a suitable relationship concerning the compressive strength of cement mortar to concrete, the experimental data compiled by Zaveh Torbet Cement Company was gathered. It is important to note that these parameters remain consistent across the time intervals of days 7 and 28.

By employing the GEP method, one can demonstrate the correlation between the compressive strength of cement mortar to concrete, as outlined in Equation 8. The pertinent parameters for Equation 8 and the GEP method can be found in Tables 1 and 2.

Table 1- introduction of simplified parameters

d_0	Blaine
d_1	Age

Table 2- The parameters used in GEP program

Function name	Label in the expression tree	Function name	Label in the expression tree
Multiplication	*	Square root	Sqrt
Addition	+	Cube root	3Rt
Division	/	Sine	Sin
Subtraction	-	Cosine	Cos
x to the power of 3	X3	Arctangent	Arctan

4. Results and discussion

To evaluate the correlation of the actual and predicted parameters and calculate the error using an equation.The stiffness functions used in the paper were as follows Equations (1-7):

- Coefficient of Determination:

$$R^2 = 1 - \left(\frac{\sum_i (A_i - P_i)^2}{\sum_i (P_i)^2} \right) \quad (1)$$

- Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2} \quad (2)$$

- Mean Absolute Percentage Error:

$$MAPE = \frac{1}{n}\sum_i \left| \frac{A_i - P_i}{A_i} \right| * 100 \quad (3)$$

- Relative Absolute Error

$$RAE = \frac{\sum_{i=1}^{n}|A_i - P_i|}{\sum_{i=1}^{n}\left|A_i - \left(\frac{\sum_{i=1}^{n} A_i}{n}\right)\right|} \quad (4)$$

- Relative Root Mean Squared Error

$$RRMSE = \frac{1}{|A_i'|}\sqrt{\frac{\sum_{i=1}^{n}(A_i - P_i)^2}{n}} \quad (5)$$

- Performance Index

$$PI = \frac{RRMSE}{R+1} \quad (6)$$

$$R = \frac{\sum_{i=1}^{n}(A_i - A_i')(P_i - P_i')}{\sqrt{\sum_{i=1}^{n}(A_i - A_i')^2 \sum_{i=1}^{n}(P_i - P_i')^2}} \quad (7)$$

Where n is the total number of data, Ai is the quantity of experimental samples and the output value of predicted samples is Pi.

Table 3- Stiffness functions for investigated GEP models

	R^2	$RMSE$	$MAPE$	RAE	$RRMSE$	R	PI
GEP model	0.793	0.0604	3.6%	0.462	4.51%	0.891	0.024

Figure 4 illustrates the error and correlation plots for the 72 mixing designs that were examined. Based on the acquired error and the correlation between the compressive strength ratio of cement mortar and concrete in both the experimental and the prediction, it can be inferred that the prediction is accurate. Furthermore, despite utilizing experimental data directly, the graph does not exhibit significant dispersion, indicating a low error in the experimental work. As can be seen, the convergence rate of the algorithm is an ideal value of 0.79. Considering that the average ratio of compressive strength of cement mortar to concrete in the samples is approximately 1.34 and the standard deviation is 0.099, the standard deviation value accounts for roughly 7% of the average. This emphasizes the data's integrity and indicates an acceptable level of dispersion.

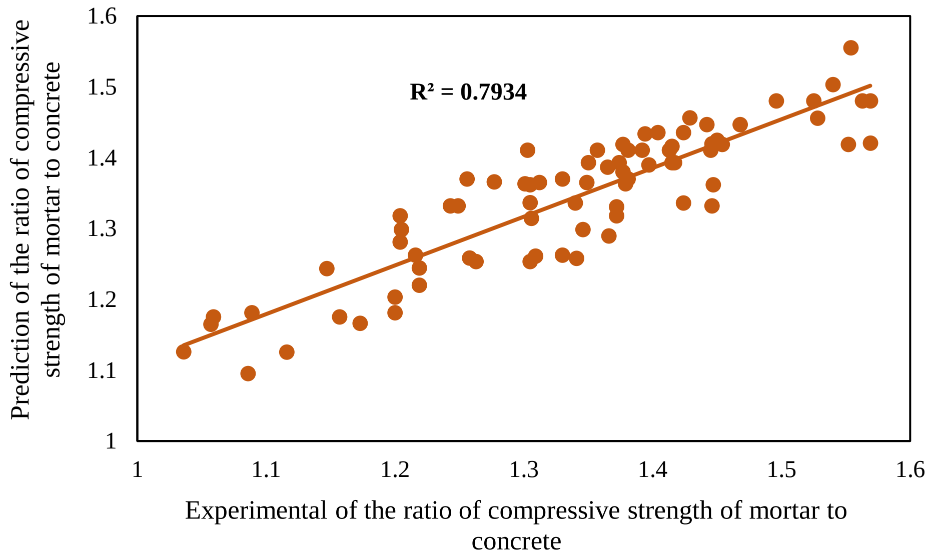
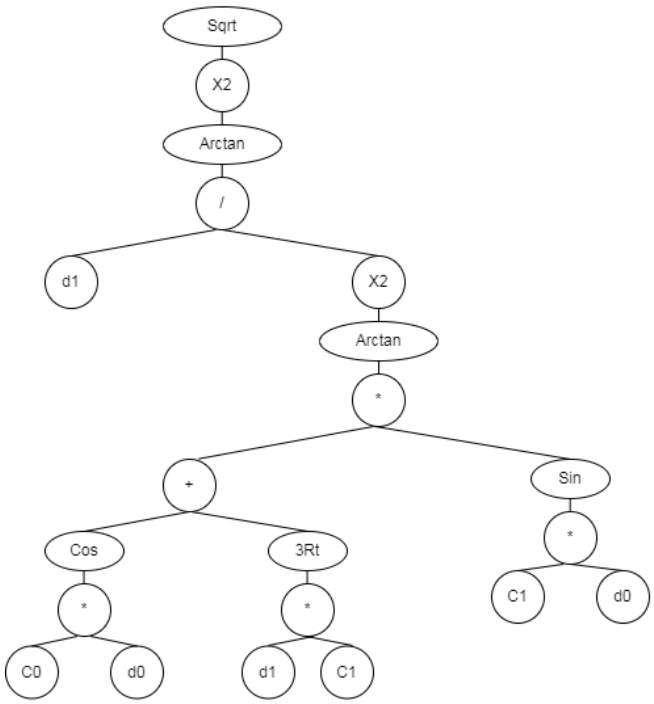
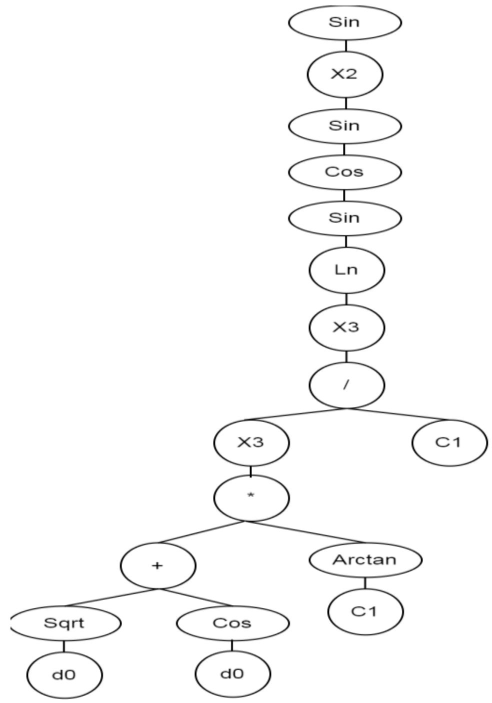


Figure 4. Correlation of the predicted values for compressive strength of mortar to concrete ratio with the experimental results

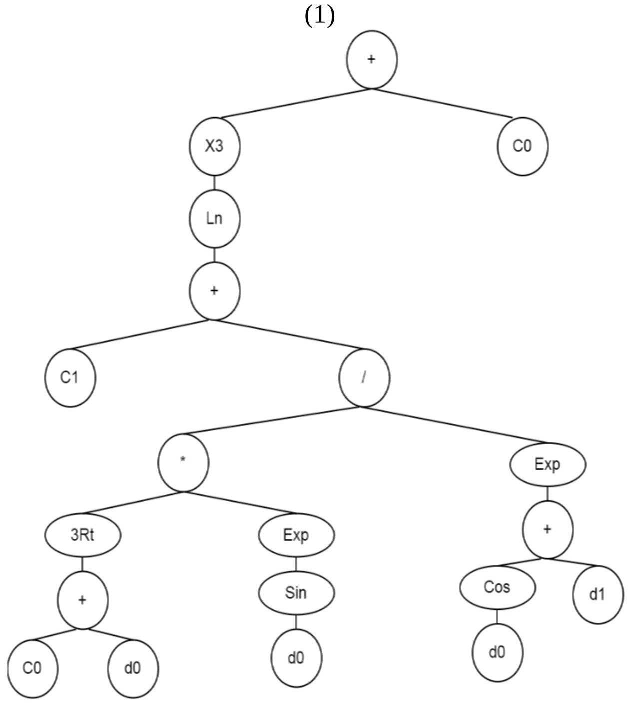
Figure 5 depicts the expression tree of the executed prediction, which has been simplified and expressed as a formula in equation 8. Equation 8 illustrates the mathematical expression upon which the prediction was founded. The aforementioned equation, although not excessively intricate, is nonetheless highly efficacious. Consequently, in future investigations entailing identical input parameters, rather than resorting to laboratory-based experimentation which necessitates substantial time and monetary resources, the deployment of this equation presents a viable alternative by which the compressive strength of mortar to concrete can be anticipated. Cognizant of Figure 5 and Equation 8, the outcomes substantiate the reliability of the prognostication. They demonstrate that the employment of four specific genes and the addition linking function prove to be fitting for accurate assessment and the attainment of an appropriate algorithm. Notably, augmenting the number of genes employed solely elongates the computation time and amplifies the complexity of the equation, devoid of any alteration to the outcome.



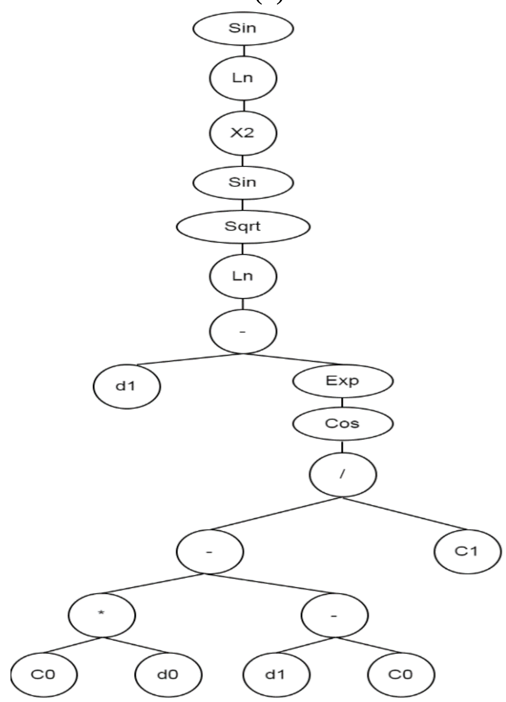
(1)



(3)



(2)



(4)

Figure 5. Expression tree of GEP model

$$\boldsymbol{GEP = (Arctan(\frac{d_1}{(Arctan(\left((Cos(-1.2d_0)) + \sqrt[3]{6.37d_1}\right)(Sin(6.37d_0))))^2}) +} \quad (8)$$

$$((\mathrm{Ln}(7.42+\frac{(\sqrt[3]{d_0-8.51})(e^{Sind_0})}{e^{(Cosd_0)+d_1}}))^3-8.51)+$$

$$(Sin(Sin(Cos\left(Sin\left(Ln\left(\frac{\left((\sqrt{d_0}+Cosd_0)(-83.55)\right)^3}{-8.85}\right)^3\right)\right)))^2)+$$

$$(Sin(Ln\left(Sin\left(\sqrt{Ln(d_1-e^{Cos\frac{(-9.32d_0)-(d_1+9.32)}{-2.34}}}\right)\right)^2))$$

5. CONCLUSIONS

The determination and evaluation of the compressive strength of mortar and concrete have a significant role in the realm of cement-based materials. As such, the accurate prediction and measurement of this parameter hold immense value. Consequently, the primary objective of this research endeavor is to examine the concurrent influence of cement fineness and sample age on the ratio of compressive strength between mortar and concrete through the utilization of the genetic method. To achieve this purpose, a comprehensive dataset comprising 72 mixing designs, encompassing 216 samples of cement mortar and concrete obtained from the Zaveh Torbat Cement Factory, has been employed. These samples were characterized by fixed proportions of water to cement and sand to cement, as well as varying degrees of cement fineness and sample age. The evaluation of the cement fineness parameter and sample age as input parameters for the model revealed that their correlation value is high and acceptable. Consequently, this model is deemed highly suitable for predicting the ratio of compressive strength of mortar to concrete. Moreover, this formula method also presents the advantage of significantly reducing laboratory costs and sample-making time. Therefore, it is recommended that future researchers consider adopting this approach.

6. ACKNOWLEDGMENT

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