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SOFT-COMPUTING MODEL FOR COMPRESSIVE STRENGTH OF MORTARS WITH BLENDED CEMENTS

Zeynep ALĞIN [1], Kasım MERMERDAŞ [1, *]

[1] Civil Engineering, Faculty of Engineering, Harran University, Şanlıurfa, Turkey

ABSTRACT

The 90 experimental data samples previously validated in the current literature regarding the compressive strength of mortars have been collected and evaluated to develop the practical soft-computing model which is presented in this study for prediction of the compressive strength of mortars with blended cements. The presented model provides many economical, technical and environmental benefits to be swiftly implemented into the practice. It is formulated based on the soft-computing techniques of genetic expression programming (GEP) by considering the model factors including as specific weight and surface of cement, water/cement ratio, testing age, the amounts of clinker, limestone, pozzolana and gypsum. The paper explains the validity of the presented model with that randomly selected experimental sub datasets available in the current literature. The findings illustrate that the presented GEP model has a favorable potential for estimating the compressive strength of mortars with blended cements.

Keywords: Blended cement, Compressive strength, Experimental database, Modelling

1. INTRODUCTION

The practical implementation of blended cements in the mortar production provides economical, technical and environmental benefits such as the reduction in clinker production and subsequent carbon dioxide emissions. In that sense, the Portland cement production is generally defined as a costly process since it requires intensive energy consumption of fossil fuels (approximately 4 GJ / ton) [1,2]. It is generally assumed that 7% of the carbon dioxide released worldwide to the atmosphere is resulted from the annual cement production of 1.6 billion tones that is based on the notion that one tonne of cement production causes atmospheric release of about one ton of carbon dioxide [3-5]. Since this is a significant part of the greenhouse gases that cause global warming, the cement production industries have considered some improvements to reduce the energy consumption and carbon dioxide emissions while cement production is increasing. One of these improvements is to utilize admixtures like ground granulated blast furnace slag (GGBFS), natural pozzolana and limestone in cement production. Accordingly, much less energy consumption is required than that of the production of Portland cement and it subsequently results in the reduction of overall cost. Since some of the material properties are also improved by these additives [6-8], the blended cements are generally preferred in the building sectors. Such advantages can be named as the increased chemical resistance, the reduction in heat evolution and permeability which are explained by many previous studies [9-14] suggesting the beneficiation of natural pozzolana as a cementitious replacement material for Portland cement in many applications. However, they are also associated with some drawbacks such as the requirement of moist-curing for prolonged periods and a decrease in strength at early ages.

Soft-computing comprises of some main components such as probabilistic reasoning, fuzzy logic, and neurocomputing which are generally known to provide the tractable, robust and low cost solutions [15]. The soft-computing models which are used in wide range of engineering problems such as design and financial applications, are based on the artificial intelligence philosophy which is based on the processes of the human mind. The fuzzy logic, genetic algorithm (GA), artificial neural network (NN), genetic programming (GP) and are known to be the most popular methods of soft-computing techniques.

*Corresponding Author: kasim.mermerdas@harran.edu.tr

GA is generally utilized for computing purpose in determination of precise or approximate solutions for finding optimum solutions or research problems and it is within the group of the evolutionary computation categorized as global search heuristics. GP is essentially the application of genetic algorithms to the computer programming [16] and it is generally used to solve discrete, non-differentiable and general nonlinear engineering optimization problems [17]. In this process the problem is defined as input and the individual solutions are searched within the program [15, 16]. Along the GP techniques, Gene expression programming (GEP) invented by Ferreira [18] is accepted as a natural development of genetic algorithms and genetic programming which evolves the programming with a random generation of the fixed-length chromosomes for each individual in the initial population [19].

The popularity of using blended cements in the mortar production has brought about the need to predict the resulting compressive strength swiftly prior to the detailed experimental studies. Therefore, the significant number of experimental datasets previously validated in the current literature [20] have been collected to generate the models accurately. They have also been evaluated to obtain the required formulations employing a well-established soft-computing procedure from the genetic programming [21-24]. The factors considered in the presented formulation are specific gravity, specific surface area (cm^2/g), water/cement ratio, testing age (days), the percentage of clinker (%),the percentage of limestone (%), the percentage of natural pozzolana (%) and the percentage of gypsum (%). The obtained model is validated by comparing the results with those randomly selected experimental data samples taken from the current literature. The conclusions drawn based on the practical use of the formulations are presented after discussion of the performance of the proposed model.

2. DESCRIPTION OF THE EXPERIMENTAL DATABASE

The limited number of researches provide the blended cement composition details correlated with the compressive strength of mortars, such as an experimental study published by Güneyisi et al [20]. The corresponding previous experimental data related with this correlation is therefore employed in the current study. In the study [20], the cements were used as ordinary and blended cements. The Portland cement was designated as CEM I 42.5 R while the other types of cements were coded as CEM II B-P 32.5 R, CEM II A-P 42.5 R for Portland pozzolana cements and CEM II A-LL 42.5, CEM II B-LL 32.5R for Portland limestone cements. For proportioning the mortar mixes, the water-to-cement (w/c) ratios of 0.420, 0.485 and 0.550 are utilized. They [20] stated that the most important mechanical performance parameter for the cement based materials is the compressive strength. Therefore they measured this parameter starting from the early ages until later ages. Since the effectiveness of blended cement on strength were still pronounced at later ages, monitoring the strength until 180 days was decided [20]. Therefore, the compressive strength development of the mortar specimens were observed at the end of 7, 28, 90, and 180 days. The selected 90 data samples used for the generation of GEP model in this paper are graphically demonstrated in Figure 1.

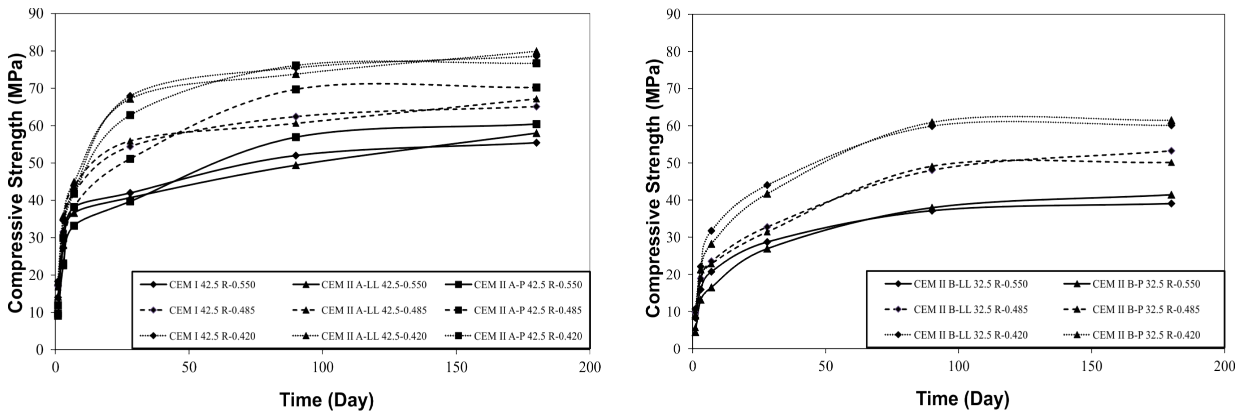

Figure 1. Experimental datasets used for the developed model (Adapted from Güneyisi et al., [20])

The datasets are classified as two parts which are the training and the testing that contains 67% and 33% of the total number of data, respectively. Training dataset is utilized for the generation of the prediction model by the software while the rest is assigned to examine the repeatability of the developed model. More specifically, in the training process the weights of model parameters are adjusted and the overfitting is prevented. Additionally, in order to test the actual predictive power of the model, the functions of validation and the testing sets are specified. The input variables considered in the modelling process are the amounts of clinker, limestone, pozzolana and gypsum; specific gravities and specific surface areas of the cements, water/cement ratios of the mortars and testing age. The ranges of the input parameters are given in Table 1.

Table 1. The variation of input parameters taken into account in this study

Input parameters		Notations	Range
d0	Clinker (%)	C	65-96
d1	Limestone (%)	L	0-27
d2	Pozzolana (%)	P	0-31
d3	Gypsum (%)	G	4-5
d4	Specific gravity	SG	2,94-3,12
d5	Specific surface (cm^2/g)	SS	3349-4613
d6	Water/cement ratio	W/C	0,42-0,55
d7	Testing age (day)	A	1-180

3. PROPOSED GEP MODEL

Gene expression programming software has been utilized for the generation of the prediction model. The parameters of the model used in the programming are given in Table 2. As demonstrated in Table 2, various mathematical operations are employed to achieve an accurate model.

Table 2. GEP parameters used for the proposed model

Parameter		f_c
P1	Function set	Simple mathematical operators, logarithmic functions, trigonometric functions, etc.
P2	Number of generation	82000
P3	Chromosomes	30
P4	Head size	8
P5	Linking function	multiplication
P6	Number of genes	5

Several modifications are conducted for the GEP parameters to obtain the optimum model having the best fitness. The trigonometric operations in the combination of the exponential functions are determined to be predominantly included in the GEP model presented in Eq. (1). The model developed by the software in its native language can also be visually analyzed through expression trees.

$$f_c = f_{c1} \times f_{c2} \times f_{c3} \times f_{c4} \times f_{c5} \tag{1}$$

Where f_c is compressive strength of mortar and f_{c1}, f_{c2}, f_{c3}, f_{c4}, and f_{c5} are the sub expression values computed from the sub expression trees (Sub-ETs) given in Figure 2. Following algebraic expression (Eqs. 2-6) are written for each of sub expression trees diagram given in Figure 2.

$$f_{c1} = \log\left[\left(d_7^{\,3} \times (d_0 + c_5) \times 10^{\sin d_0}\right)\right] \tag{2}$$

$$f_{c2} = d_6 - \arctan\left[\frac{d_0 + 2\times d_7 + 3\times \tan d_3}{6} + (d_1 - c_4)\right] \tag{3}$$

$$f_{c3} = d_6 \times \left(\frac{\frac{d_7}{d_0} + 10^{d_6} + d_6^{\,2}}{3}\right) - d_4 \tag{4}$$

$$f_{c4} = d_4 + \frac{3}{(d_1 - d_7)\times d_3} \tag{5}$$

$$f_{c5} = \cos\left[\frac{2}{(c_5 - d_2) + d_3 - 2\times \tan(d_6)} + d_2\right] \tag{6}$$

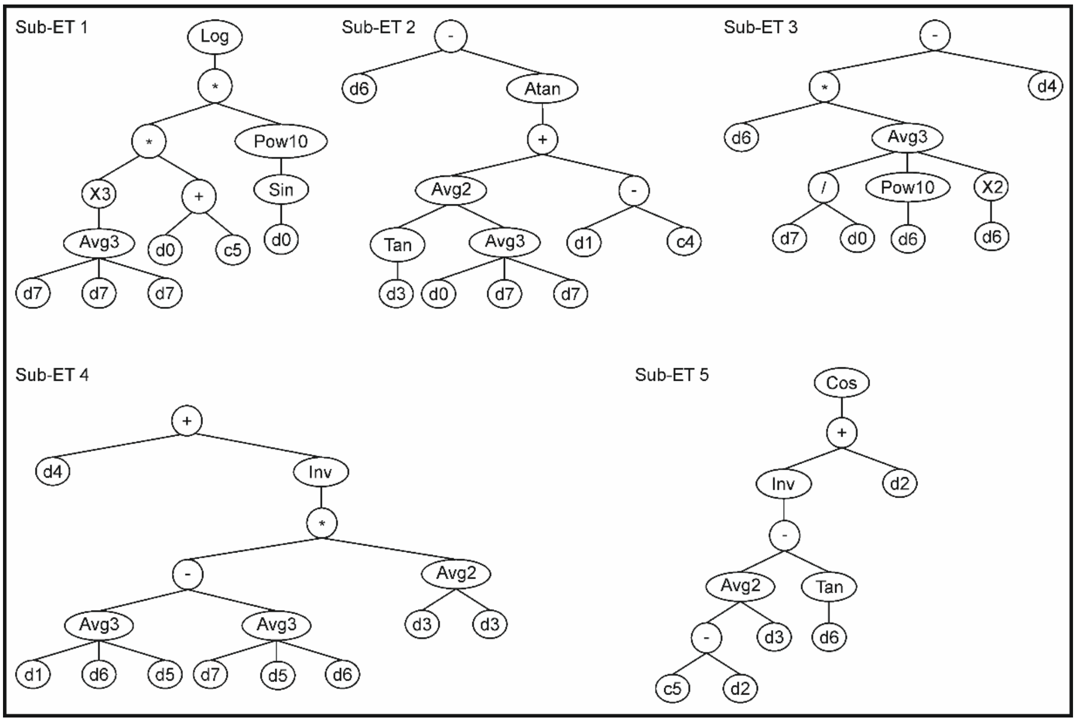

Figure 2. The GEP model's expression tree (c5= 11.961222 for SubET1, c4= 10.095787 for SubET2, c5= 2.744547 for SubET5)

The estimation ability of the generated GEP model in Eq. (1) was graphically shown in Figure 3 for both the training and the testing data sets. The variations of the predicted and the experimental data are strongly correlated, with R values of 0.991 and 0.976 for the training and the testing databases, respectively. Moreover, the closeness of the values of the correlation coefficients may also be considered as proof for the robustness and repeatability of the generated mathematical model.

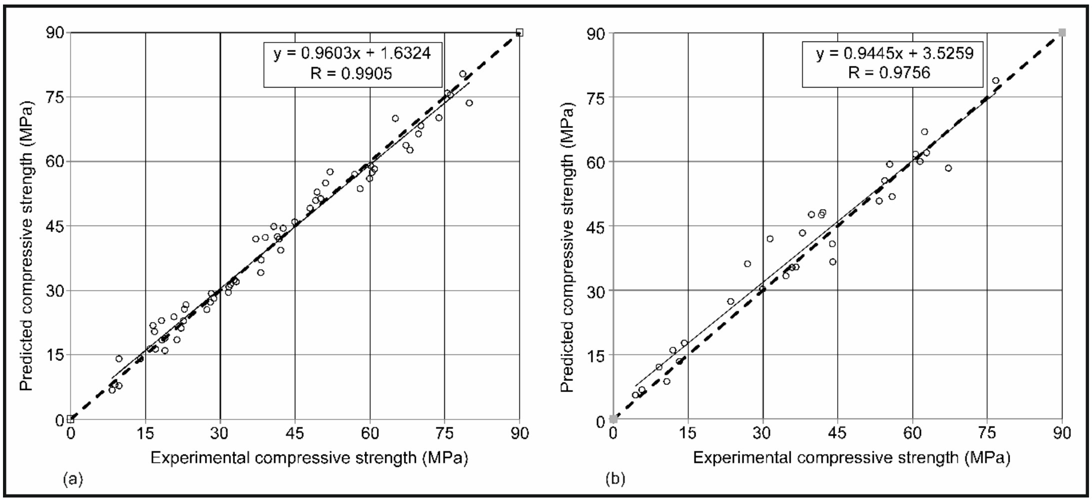

Figure 3. Evaluation of the experimental data and the predicted values from the proposed GEP model for the compressive strength of mortars with blended cement; a) the training set and b) the testing set

4. PERFORMANCE OF THE PROPOSED GEP MODEL

The normalized results obtained by dividing the predicted values to the actual data are evaluated and depicted in Figure 4 to indicate the prediction performance of the developed model. Based on the normalized values, the perfect estimation performance is equal to 1.0. The values below and above this value show the underestimate and overestimate performance, respectively. The border lines are also drawn for ± 10% values to clearly demonstrate the trend of the data. Figure 4 shows that the majority of the data remains between the limiting values for the compressive strength greater than 25 MPa. For the values lower than 25 MPa the prediction is mostly overestimated (%48). However, only 14% of the estimated data corresponding to the actual compressive strength values between 25-80 MPa demonstrated overprediction. 5% of the predicted compressive strength values were lower than the specified limit. As seen from the figure generally the overestimated values were obtained for this range. However above 25 MPa, the prediction error is generally less than 10%.

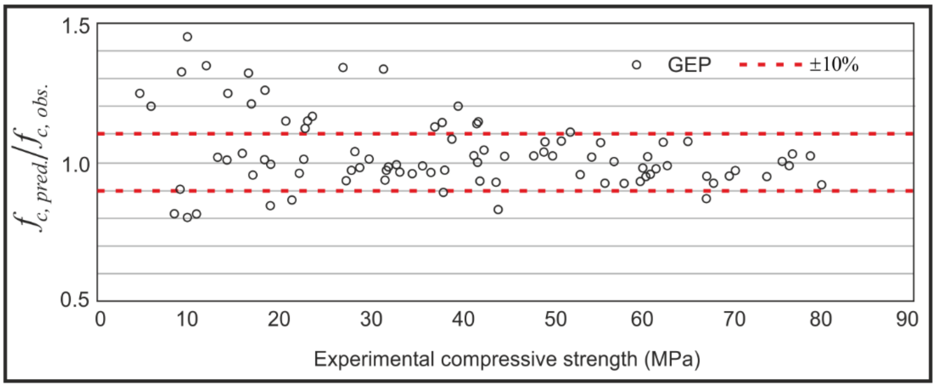

Figure 4. Prediction performances of the proposed GEP model

Further evaluation of the estimation performance of the generated model can also be undertaken by means of statistical assessment. Thus, the following statistical parameters are calculated using Eqs. 7–9 and the obtained results are presented in Table 3. As can be seen in Table 3, the low error values are obtained in terms of accuracy and precision of the model's prediction.

$$\text{Mean absolute percentage error (MAPE)} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{m_i - p_i}{m_i}\right| \times 100 \quad (7)$$

$$\text{Mean square error (MSE)} = \frac{\sum_{i=1}^{n}(m_i - p_i)^2}{n} \quad (8)$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{n}(m_i - p_i)^2}{n}} \quad (9)$$

Where, the notations of *m* and *p* refer to the measured and the predicted values, respectively

Table 3. Statistical analysis of the generated model

Parameters	Training set	Testing set
MSE	8.06	21.14
MAPE	7.57	12.93
RMSE	2.84	4.60
Correlation coefficient (R)	0.991	0.976

5. VERIFICATION OF GEP MODEL

The prediction capability of the generated model has also been verified using the data from the technical literature. The values obtained from Tosun et al. [25] and Çelik et al. [26] were not included in the data set used for derivation of the proposed GEP model. Figure 5 depicts the experimental values versus the predicted values obtained by the proposed model. The figure demonstrates that a relatively good agreement is obtained from the proposed GEP model since the linear regression lines for these experimental data closely follows the diagonal line shown in Figure 5. As can be seen, high values of coefficients of correlation were obtained for the referred data from Tosun et al. [25] and Çelik et al. [26].

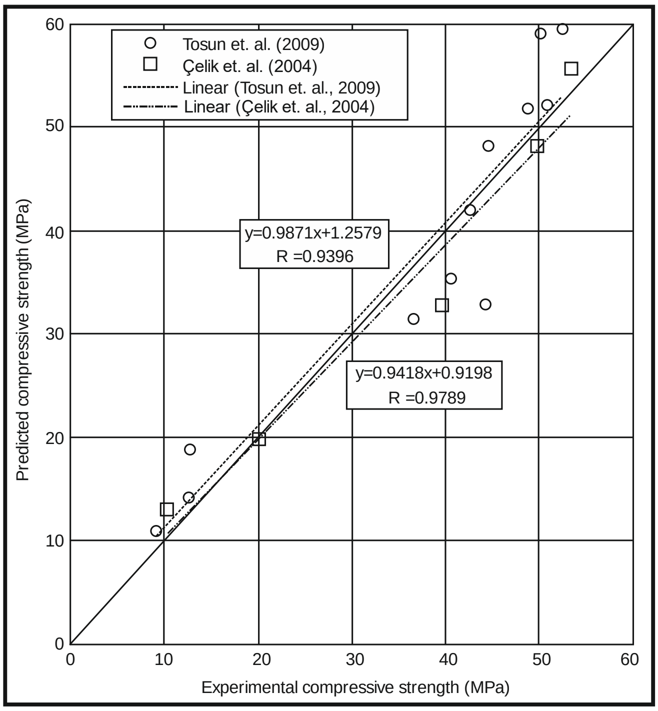

Figure 5. The comparison between the data in literature and the prediction values from the proposed GEP model

The level of correlation observed from the figure can also be considered strength of prediction capability of the proposed model. From this point of view, the idea of using this mathematical relation in development of softwares with user friendly interface may be realized.

6. CONCLUSIONS

The researchers and/or practitioners may need to foresee the outputs from the experimental program. For this purpose there have been various studies to generate the prediction models to estimate some engineering properties of the cement based materials.

The summary of the conclusions drawn from the paper are as follows:

- The mathematical model presented in this paper highlights the fact that GEP based mathematical expression can be used to predict the compressive strength of mortars produced with various blended cement types.

- The experimental data presented by Güneyisi et al. [20] were used to derive a prediction formula for compressive strength of mortars produced with blended cement.

- The actual values have been compared with the prediction results from the proposed GEP model. The analyses have proven that the formula can be accepted as a handful tool for prediction purpose.

- Several tests have also demonstrated that sub-sets of the data provide results which are almost identical to the predicted values. These validations suggest that the presented GEP model is valid within the more general cases for the varying parameters for the defined range of specific weight and fineness specific surface area of cement, water/cement ratio, testing age, the amounts of clinker, limestone, pozzolana and gypsum. In this respect, the proposed GEP model represents a significant step forward in the prediction of compressive strength of mortars with the blended cements.

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