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A Comparative Study of Machine Learning Methods for Compressive Strength of Concrete

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Abstract - This paper introduces a comparative study for the compressive strength of concrete by employing machine learning approaches such as Genetic Programming (GP) and Artificial Neural Network (ANN). The simulation of concrete strength is strongly needed to better understand its behaviours under different conditions and loads. Since many studies predict the comprehensive strength of conventional concrete from hardened characteristics, based on the data points gathered from different experimental tests, empirical models have been developed and verified in the past years. Proposed models are more reliable if the numbers of tests increase and their repeatability increase as well. However, these models are designed for a specific range of concrete strengths. On the other hand, numerical models are more reliable since they are devised based on theoretical rules which could consider behaviours of concrete under different loading paths. But, the validation of these models is made by different loading paths with different configurations that result in costly experiments and both models use only principal stresses and strains in their formulation. Employing machine learning approaches instead of traditional models makes it possible to develop a better understanding of the compressive strength of concrete. Hence, the focus of this paper is the application of machine learning process and their suitability to model concrete compressive strength compared with early models obtained from the literature and compared with some conventional approaches.

Keywords**:** genetic programming, artificial neural network, concrete strength, machine learning methods.

1. Introduction

Nowadays, the single compressive strength still describes the behaviour of concrete, but its complex nature is pushing towards to a more comprehensive and accurate method. In the past decades, the compound stress situations were studied, and many models have been proposed.

To solve engineering problems, many studies use empirical, analytical and numerical methods that are simplified by different assumptions and, therefore, in most cases, accompanied by approximations. These simplifications have resulted in high rates of errors which produce large discrepancies between the actual and the calculated results.

Some models, such as Rankine, von Mises, Tresca and Mohr-Coulomb, were introduced early in the studies of concrete [1-2]. These models were easy to use, but the behaviour description was not accurate. Later on, more complex models - for instance Bresler and Pister, Willan and Warnk and Ottosen - [3-6] were developed. These approaches allow for a more truthful description of the compressive strength, but the complexity to predefine the model complicate their use. With the development of machine learning methods, the application of such approaches to develop new models for concrete strength became interesting [7].

Several studies used GPs and ANNs for predicting the strength of different types of concrete. The machine learning techniques directly learn from raw experimental data inserted and release the functional relationships among the data, even if the underlying relationships are unknown or the physical meaning is difficult to be explained. The machine learning techniques will be more appropriate to be applied for modelling the complex behaviour of many engineering problems with extreme variability in their natures.

Meanwhile, machine learning approaches, such as GP models, can use the available databases in the literature, with no need for the evaluation by specific experimental tests. These models consider other effective parameters in concrete behaviour, and their accuracies depend on the size and variety of the database. Afterwards, these models could be used as a proper tool for the validation and verification of the existing models used by the building codes.

Hence, the main objective of this study is to resume and to compare machine learning approaches, such as Genetic Programming (GP) and Artificial Neural Network (ANN), available in the literature. The motivation of this paper is to investigate the suitability of the machine learning process for modelling concrete compressive strength, especially concerning the accuracy and efficiency as well as their potential to cope with uncertain experimental data.

2. Genetic Programming Methods

Genetic Programming (GP) is an advanced subcategory of the machine learning methods. Their main ability is to model the mechanical behaviour of concrete without any prior assumptions. In this manner, the proposal of Koza (1992) [8] might be helpful for a newly developed method for modelling of the structural engineering issues. GP generates the solutions which are computer programs rather than binary strings. It could be accounted as a supervised machine learning technique while searching program space instead of a data space [7].

Most of the genetic operators used in Genetic Algorithms (GA) can also be implemented in GP, with minor changes. The main difference between GP and GA is the represent solution. The GP solutions are computer programs represented as tree structures and expressed in a functional programming language. [9].

The GP algorithm starts the evaluation of the individuals' fitnesses once a population of individuals have to been created randomly. Then, it selects individuals for reproduction, creating a higher probability of selection. These individuals are directly copied into the next generation. Then, the crossover operation is applied to exchange the genetic materials between future programs. This procedure will choose on a branch of each program later on. Each program will be a set of terminals and functions are selected in order to create two new solutions. During the mutation process, a terminal from a model is randomly chosen to be mutated, occasionally. If the randomly selected node is a function, depending on the type of mutation, a new function is assigned [7].

3. Artificial Neural Network Methods

Artificial Neural Networks (ANNs) have emerged as a result of the simulation of the biological nervous system. The ANN method was founded in early 1940 by McCulloch and co-workers [10-11]. They are composed of parallel processing elements which are comparable, in their purpose, to human neurons and are tied together with connection weights corresponding to the human brain synapses. The idea of encompassing many different engineering issues lies in the modelling and assessment of the relationship between a set of input and output variables [12].

Recently, many studies have been using various methods such as analytical modelling, mechanical modelling, statistical methods and artificial intelligence [13-16] for predicting the strength of concrete incorporating various ingredients, including ANNs. Artificial Neural Networks techniques are amongst the areas in artificial intelligence that have grown fast and gained popular engineering applications and have been employed in many civil engineering applications such as detection of structural damage, structural system identification, material behaviour modelling, groundwater monitoring, foundation settlement prediction, concrete mix proportioning and concrete strength prediction [17-20].

ANNs are capable of learning and generalising from instances and experience to produce accurate solutions to problems, even when input data features contain errors and are incomplete. This makes ANNs a powerful instrument for solving some of the complex engineering problems. The processing elements of a neural network are similar to the neuron in the brain, which consists of many simple computational elements arranged in layers [21].

4. Strength models of concrete using machine learning methods

Yeh [22] investigated the potential of using neural networks to determine the effect of fly ash replacements on early and late compressive strength of low and high-strength concretes. The research shows the need for a much smaller number of experiments to obtain meaningful data, and the high correlations between the compressive strength and the component composition of concrete can be developed using ANNs. The percentage of the strength of concrete containing fly ash to the strength of concrete without fly ash at the same age is significantly reduced as the fly ash replacement increases.

Gandomi and Alavi [9] developed a GP model to predict the uniaxial compressive strength of concrete. It is known that the distribution of the predictor variables is not uniform. For the cases where the frequencies of the variables are higher, the derived models are expected to provide better predictions. At this same study, the authors developed an ANN model to predict the uniaxial compressive strength of concrete. The used database contained 1133 concrete compressive strength test results as presented by Yeh [22-23].

Gandomi et al. [24] proposed a new design equation for the prediction of shear strength of reinforced concrete beams without stirrups using a linear genetic programming methodology. The shear strength was formulated in terms of several effective parameters such as shear span to depth ratio, concrete cylinder strength at the date of testing, amount of longitudinal reinforcement, lever arm, and maximum specified size of coarse aggregate. The results indicate that a derived model is an effective tool for the estimation of the shear capacity of members without stirrups.

Bayazidi et al. [25] presented a new multigene genetic programming (MGGP) approach for the estimation of the elastic modulus of concrete.The technique models the elastic modulus behaviour by integrating the capabilities of standard genetic programming and classical regression. The research aims to derive precise relationships between the tangent elastic modulus of normal and high strength concrete and the corresponding compressive strength values. Another contribution of this study is to develop a generalized prediction model for the elastic modulus of both normal and high strength concrete. A comprehensive comparative study was conducted to verify the performance of the models.The proposed models perform superior to the existing traditional models, as well as those derived using other powerful soft computing tools.

Babanajad et al. [26] proposed a model to correlate the concrete true-triaxial strength to mix design parameters and principal stresses, with no need of conducting any time-consuming laboratory experiments. A comprehensive true triaxial database was obtained from the literature to build the proposed models, subsequently implemented for verification purposes. The study demonstrates superior performance in comparison to other existing empirical and analytical models.

Getahun et al. [21] developed an ANN model for predicting the strength of concrete incorporating rice husk ash and reclaimed asphalt pavement as partial replacements of Portland cement and virgin aggregates respectively. The ANN model predicted the compressive and tensile splitting strengths with prediction lows error values. The model overpredicted the compressive strength on average, whereas it underpredicted the tensile strength. The results indicate that the ANN is an efficient model to be used as a tool for predicting the compressive and tensile strengths of concrete.

Kaplan et al. [27] also estimate the compressive strength using artificial neural networks. The values of the slopes of the regression lines for training, validating and testing datasets were 0.9881, 0.9885 and 0.9776, respectively. Forty mixes were selected in order to create a simulation of the ANN model developed, and the model's ability to estimate was explored. The model was quite successful in estimating the compressive strength values.

5. Comparative Study

Prediction statistics of the machine learning models and other empirical/analytical equations found in the literature could be a representation of how well the proposed models perform in comparison with others. In the following, the machine learning based proposed models are compared against others found in the literature (Table 1). In total, 15 models were compared: 7 models allocated as GP models, 3 models were chosen from empirical/analytical references and 5 ANN models. The results were collected in the literature presented in Section 2 above. Since these results were from different references, in some cases, one or two of *RMSE, MAE*, *R* and ρ statistical parameters were missing.

To evaluate the capabilities of the models, four different statistical error parameters were considered in the comparison: *RMSE, MAE*, *R* and ρ. These four parameters are widely used and respectively indicate the Root Mean Square Error, Mean Absolute Error, Correlation Coefficient and Correlation Index given in the form of following relationships:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n}} \tag{1}$$

$$MAE = \frac{\sum_{i=1}^{n}|h_i - t_i|}{n} \tag{2}$$

$$R = \frac{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)\cdot(t_i - \overline{t_i})}{\sqrt{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)^2 \cdot \sum_{i=1}^{n}(t_i - \overline{t_i})^2}} \tag{3}$$

$$\rho = \frac{RMSE}{1 + R} \tag{4}$$

in which h_i and t_i are, respectively, the actual and the calculated output for the i^{th} output; $\overline{h_i}$ and $\overline{t_i}$ are the average of the actual and the predicted outputs, respectively; and, n is the number of samples.

Table 1: Comparison of the proposed models.

Researcher	*RMSE*	*MAE*	*R*	ρ
Bresler and Pister (1958) [4]	137.5	100.8	0.559	88.20
Ottosen (1977) [5]	26.84	19.90	0.890	14.20
Willam and Warnke (1975) [6]	47.73	28.17	0,840	25.94
ANN method (Yeh 2006) [22]	5.7	-	0.966	2.90
GP method I (Gandomi and Alavi, 2011) [9]	-	6.14	0.881	-
GP method II (Gandomi and Alavi, 2011) [9]	-	5.71	0.906	-
ANN method I (Gandomi and Alavi, 2011) [9]	-	4.31	0.979	-
ANN method II (Gandomi and Alavi, 2011) [9]	-	4.37	1.043	-
GP method (Gandomi et al. 2014) [24]	0.41	0.61	0.923	
GP method (Bayazidi et al. 2014) [25]	-	-	0.629	2.61
GP method I (Babanajad et al 2017) [26]	13.58	9.82	0.984	6.84
GP method II (Babanajad et al 2017) [26]	7.87	5.91	0.990	3.95
GP method III (Babanajad et al 2017) [26]	11.14	7.11	0.988	5.60
ANN compressive (Getahum, et al 2018) [21]	0.64	0.48	-	-
ANN compressive (Getahum, et al 2018) [21]	0.07	0.05	-	-
ANN method (Kaplan, et al. 2019) [22]	6.24	4.85	0.996	-

6. Conclusion

The study has an objective of summarising and comparing Genetic Programming and Artificial Neural Network with classical models such as Bresler and Pister, Willan and Warnk and Ottosen. This paper considered the suitability of the machine learning process for modelling concrete compressive strength especially concerning accuracy and efficiency as well as their potential to cope with uncertain experimental data.

The main advantage of the machine learning approaches is that they are model-free approaches which means that they do not put the data in a specific *mold* or drive it to a certain *shape*. The comparison showed the limitation of the conventional models compared with machine learning models.

One of the capabilities of GP based models in distinction to the conventional models is that they can use the mix design properties of concrete in order to model the strength of the concrete while there is no need to conduct experimental tests. In the other hand, since the conventional models were derived through the empirical and analytical methods, they were unable to consider many of the mix design properties. As a highlighted point, in some cases, the proposed GP based models directly consider the effect of specimen age in their final formula. As more data become available, the GP based models can be improved to make even more accurate predictions for a wider range of applications.

The main shortcoming of ANN is related to its "black box" nature and the fact that the relationship between input and output variables that are not easily accessible to users. ANNs models predict better than traditionals methods. It could also deal with sufficient factors to influence the concrete strength development.

The Artificial Neural Networks methods have been successful in solving rather difficult engineering problems, resulting in high efficiencies. The ANNs have been utilized to discover different features of cement based materials such as concrete. As much as ANNs are successful in predicting concrete behaviour, they are not as successful in producing practical prediction equations.

In contrast, Genetic Programming owns the ability to model the mechanical behaviour of concrete without any prior assumptions whatsoever regarding material behavior. GP proposes simplified prediction equations without any assumption regarding the form of the existing relationships. This characteristic rises up GP over the conventional statistical or ANN techniques.

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