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Research paper

Predicting compressive strength of lightweight foamed concrete using extreme learning machine model

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A R T I C L E I N F O

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A B S T R A C T

In this research, a machine learning model namely extreme learning machine (ELM) is proposed to predict the compressive strength of foamed concrete. The potential of the ELM model is validated in comparison with multivariate adaptive regression spline (MARS), M5 Tree models and support vector regression (SVR). The Lightweight foamed concrete is produced via creating a cellular structure in a cementitious matrix during the mixing process, and is widely used in heat insulation, sound attenuation, roofing, tunneling and geotechnical applications. Achieving product consistency and accurate predictability of its performance is key to the success of this technology. In the present study, an experimental database encompassing pertinent data retrieved from several previous studies has been created and utilized to train and validate the ELM, MARS, M5 Tree and SVR machine learning models. The input parameters for the predictive models include the cement content, oven dry density, water-to-binder ratio and foamed volume. The predictive accuracy of the four models has been assessed via several statistical score indicators. The results showed that the proposed ELM model achieved an adequate level of prediction accuracy, improving MARS, M5 Tree and SVR models. Hence, the ELM model could be employed as a reliable and accurate data intelligent approach for predicting the compressive strength of foamed concrete, saving laborious trial batches required to attain the desired product quality.

1. Background

Foamed concrete is a versatile material consisting of either Portland cement paste or mortar, with a homogeneous cellular structure created via inducing air voids during the mixing process [1]. Being lightweight with desirable sound attenuation and heat insulation characteristics, the foamed concrete can be made more sustainable and eco-efficient through partial or full replacement of fine aggregates with recycled by-products [2]. To ensure its optimal benefits, there have been attempts to enhance the mechanical properties of foamed concrete, particularly for structural purposes beyond the traditional filling and insulation applications.

The compressive strength of foamed concrete dramatically decreases with a reduction in its density. The water-to-cement and sand-to-cement ratios, curing regime, distribution of voids and type of foaming agent used are the key parameters affecting the mechanical strength of foamed concrete [3]. Kearsley and Wainwright [4] reported that the compressive strength of foamed concrete is primary a function of its dry density, while the percentage of fly ash partial replacement for cement had little effect on compressive strength. Hilal et al. [5] investigated the effect of different additives on the compressive strength of foamed concrete, the influence of the air-void size and shape parameters, and changes its actual microstructure. This study concluded that the enhancement of the void structure can contribute to the strength of the foamed concrete.

Several other studies have investigated properties of foamed

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concrete, with or without additives and admixtures including mechanical strength [4,6–9], durability [10–13], pore structure [14–16], fracture properties [17,18] and its structural properties in a composite system [2,19]. Such studies have investigated the ability to predict the compressive strength of foamed concrete from its mixture constituents, with a general view to attain a superior quality of the product. For instance, Narayanan and Ramamurthy [20] and Nehdi et al. [21] have suggested that the influence of mixture constituents (by its volume) of cellular concrete on its compressive strength can be represented by Feret's formula. This in fact, relates the compressive strength (f_{cc}) to water-to-cement ratio (w/c) and air-to-cement ratio (a/c) as follows:

$$f_{cc} = k\left(\frac{1}{1+\frac{w}{c}+\frac{a}{c}}\right)^{m} \tag{1}$$

where k and m are empirical constants.

Narayanan and Ramamurthy [20] reported three proposed strength prediction models based on the porosity of aerated concrete. In a study to investigate the effect of the water-to-cementitious materials ratio on the void system and mechanical properties of foamed concrete, [78] proposed the following relationship between the compressive strength (f_{cc}) of foamed concrete and the air content (A) as a function of the compressive strength of the cement paste (f_c):

$$f_{cc} = 1.048\, f_c\, (1 - A)^{2.793} \tag{2}$$

The following equation expresses the relationship between compressive strength (fc) of cement paste and effective water-to-cement ratio (w/c) as well as curing time (t):

$$f_c = 88.04 + 6.569\ln(t) - 130.5\, w/c \tag{3}$$

Moreover, the effect of the binder ratio on the compressive strength of foamed concrete was derived by Kearsley and Wainwright [4] as follows:

$$f_{cc} = 1.172\, f_c \propto_b^{3.7} \tag{4}$$

where: f_{cc} is the compressive strength of foamed concrete, f_c is the compressive strength of the cement paste calculated from Eq. (3) and α_b is the binder ratio (by volume).

In view of the above formulations, the prediction of compressive strength relies on a number of parameters, whose contribution to the overall material needs to be optimized. Due to the large differences between the calculated and actual compressive strength results, Kearsley and Wainwright [4] concluded that there may be other factors than age, effective water-to-cement ratio and binder ratio that have significant effect on the compressive strength of foamed concrete. They observed that such differences between calculated and actual strengths increased with decreasing density (i.e. with increasing foam volume), indicating that the void system (total volume and size distribution of voids) are influential on the compressive strength of foamed concrete. Assuming that the cement paste in the foamed concrete has the same strength of that of the un-foamed mortar and noting that the effect of the age and w/c are already taken into account in Eq. (3), the effect of the foam volume can be taken into account by adopting the density ratio, which is the ratio between the dry density of the foamed concrete and that of the un-foamed mixture before adding the foam.

The relationship between compressive strength of foamed concrete (f_{cc}) and the dry density ratio (α_d) was derived via regression analysis by Kearsley and Wainwright [22] as follows:

$$f_{cc} = f_c(-0.324 + 1.325 \propto_d)^2 \tag{5}$$

Earlier research by Nehdi et al. [21] implemented novel soft computing approaches (i.e. artificial neural networks (ANN)) in predicting the compressive strength of pre-formed foam cellular concrete. They applied four key input variables, including the cement content, water-to-cementitious materials ratio, sand-to-cementitious materials ratio and foam-to-cementitious materials ratio. It was found that the ANN model provided a powerful tool for predicting the compressive strength of foamed concrete. In a somewhat related study, Khan [23] also reported the applicability of ANN for the prediction of the compressive strength, tensile strength, gas permeability and chloride ion penetration of high performance concrete. A comparative investigation between ANN model and linear regression model for estimating the compressive strength of steel fiber-added lightweight concrete was carried out by [24]. In this work, it was found that the ANN model outperformed the linear regression model yielding more accurate estimation. Altun, Kişi [25] estimated the compressive strength of concrete incorporating various amounts of blast furnace slag and fly ash, based on the properties of the additives and values obtained by non-destructive testing rebound number and ultrasonic pulse velocity. The application of ANN to predicting compressive strength has thus shown great potential, particularly for calculating nonlinear functional relationships, for which classical methods cannot be applied. Many other researchers have explored the applicability of ANN models in predicting the concrete strength [26–29]. All reported studies emphasized the reliability of ANN in predicting compressive concrete strength. Yet, such models remain ``black box'' tools, requiring internal parameters, along with time consuming training and validation.

Over the past five years, the implementations of the non-tuned machine learning model ``i.e., ELM'' have shown a noticeable progress in multidisciplinary of science and engineering fields. This is due to its advantages (particularly over conventional artificial neural network algorithms) such as the randomly initiated hidden neurons without the need for iterative tuning process for free parameters or connections between hidden and output layer. Consequently, ELM is remarkably efficient to reach a global optimum, following universal approximation capability of single layer feed-forward network [30,31]. Also, this model is featured by the efficiency and generalization performance over traditional learning algorithms (*e.g.*, SVMs or ANNs) as revealed in the estimation problems in many different fields (e.g., [32–35]). For more details on advanced theoretical perspectives, including the interpolation theory, universal approximation capability and generalization ability of ELMs, the readers can refer to many other excellent reviews (*e.g.*, [30,36,37]).

In the present research paper, the implementation of the machine learning regression model, namely extreme learning machine (ELM) is developed for the first time to predict the compressive strength of foamed concrete. The efficiency of the ELM model is verified against couple of highly robust regression models including multivariate adaptive regression splines (MARS), M5 Tree and support vector regression (SVR). The modeling is conducted using an experimental database retrieved from previous published studies available in the open literature.

The rest of the article is structured in the following way: In the next section, the machine learning models considered in this paper are described. In Section 3, the description of the experimental dataset is presented. The model's development and prediction skills metrics are indicated in Sections 4 and 5. The application and results are discussed in Section 6. Finally, the conclusion and remarks are presented in the last section of conclusions.

2. Methodological background

2.1. Extreme learning machine

The Extreme Learning Machine (ELM), is a neural network-based model, and an innovative new data-driven tool that utilizes a state-of-the-art single-layer feed forward network (SLFN) algorithm to yield a closed-form solution to the output weights through a least squares solution (after fixing the hidden layer weights and biases). It is drawn from a continuous probability distribution function [31] rather than using an iterative solution adopted by a conventional feed-forward ANN model. The major advantage of the ELM model is the lesser complexity

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