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Evaluation of the splitting tensile strength in plain and steel fiber-reinforced concrete based on the compressive strength

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HIGHLIGHTS

- Splitting tensile strength of concrete was predicted using different methods.
- Plain and steel fiber-reinforced concretes were studied.
- ML techniques have definitely a better performance compared with NLR.
- Compressive strength is the most statistically significant parameter.

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ABSTRACT

Compressive strength (f_c) and splitting tensile strength (f_{spt}) of concrete are two important parameters in structural design. Due to the complexity, cost, and time-consuming nature of performing tensile tests, many researchers are interested to predict the value of this property in a simplified but accurate manner. This paper presents non-linear regression (NLR) analysis, artificial neural network (ANN), support vector machine (SVM) and M5′ model tree (MT) techniques to predict the tensile strength (f_{spt}) of concretes made with and without steel fiber reinforcement. Error measures were used to compare the performance of different models including the models developed in this study and those developed by other researchers. Results indicated that non-linear regression analysis, artificial neural network, support vector machine, and model tree algorithms can predict the splitting tensile strength of concretes made with and without steel fiber reinforcement with satisfactory accuracy. However, machine learning techniques such as ANN, M5′ model tree and SVM provided superior models compared to NLR analysis.

1. Introduction

Compressive strength (f_c) and splitting tensile strength (f_{spt}) of concrete are two important parameters in structural design. Although concrete is not normally designed to sustain tensile forces, the knowledge of tensile strength becomes important as it is used to estimate the level of load under which cracking will initiate. From the design perspective of plain and non-reinforced concrete (e.g., dams, slabs and airfields under bending stresses), the ability of the concrete to withstand tensile forces is more important than its capacity in sustaining compressive forces [1]. Tensile strength of concrete can be measured by various tests such as direct tension, flexure and splitting tensile tests. However, it should be noted that different types of tests have yielded different results of tensile strength. In addition to its high variability, the complexity, cost and time-consuming nature of the tests have suggested many scientists and engineers to assess this property through the compressive strength [1]. Some of the developed relationships between splitting tensile strength (f_{spt}) and compressive strength (f_c) are given in Table 1.

Each equation listed in Table 1 was derived from experimental results on different types of concretes as described in the comments. Therefore, the application of these equations might not be reliable in other conditions. For example, Kim et al. reported that Eqs. (3) and (9) have overestimated the f_{spt} of concretes with low compressive strength but underestimated the f_{spt} of concretes with compressive strength over 20 MPa. In addition, they found that Eqs. (4) and (14) could accurately estimate the f_{spt} of concretes with compressive strength under 20 MPa but tended to underestimate the f_{spt} of concretes with compressive strength over 20 MPa. The tensile-strength predictive models presented by Eqs. (17) and (18) in Table 1 were developed for concretes with steel fiber reinforcement as it was found that the introduction of fibers markedly

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Table 1
Some of the equations found in the literature relating the splitting tensile strength and the compressive strength in concrete.

Equation	Statistical model	Reference	Remarks/comments
(1)	$f_{spt} = \frac{f_c}{0.1f_c+7.11}$	Zain et al. [1]	High performance concrete; $f_c > 40$
(2)	$f_{spt} = 0.59f_c^{0.5}$	ACI 363R-92 [2]	$21 < f_c < 83$
(3)	$f_{spt} = 0.56f_c^{0.5}$	ACI 318-99 [3]	
(4)	$f_{spt} = 0.3f_c^{2/3}$	CEB-FIB [4]	
(5)	$f_{spt} = 0.56f_c^{0.5}$	Mokhtarzadeh and French [5]	$48 \leqslant f_c \leqslant 103$
(6)	$f_{spt} = 0.32f_c^{0.63}$	Mokhtarzadeh and French [5]	$48 \leqslant f_c \leqslant 103$
(7)	$f_{spt} = 0.272f_c^{0.71}$	Carino and Lew [6]	
(8)	$f_{spt} = 0.313f_c^{0.667}$	Raphael [7]	Normal concrete; for $f_c \leqslant 40$ MPa
(9)	$f_{spt} = 0.462f_c^{0.55}$	Ahmad and Shah [8]	$15 \leqslant f_c \leqslant 84$
(10)	$f_{spt} = 0.47f_c^{0.59}$	Gardner et al. [9]	$3 \leqslant f_c \leqslant 46$; Type I cement concretes
(11)	$f_{spt} = 0.46f_c^{0.6}$	Gardner et al. [9]	$13 \leqslant f_c \leqslant 72$; Type III cement concretes
(12)	$f_{spt} = 0.34f_c^{0.66}$	Gardner [10]	$4 \leqslant f_c \leqslant 57$; best-fit relationship for Type I, Type III, and cement/fly ash concrete
(13)	$f_{spt} = 0.33f_c^{0.5}$	Gardner [10]	$4 \leqslant f_c \leqslant 57$; best-fit relationship for Type I, Type III, and cement/fly ash concrete
(14)	$f_{spt} = 0.294f_c^{0.69}$	Oluokun et al. [11]	$3.5 \leqslant f_c \leqslant 63$; normal-weight concrete
(15)	$f_{spt} = 0.387f_c^{0.63}$	Arıoglu et al. [12]	$4 \leqslant f_c \leqslant 120$; proposed for Type I, Type III, cement/fly ash, cement/bottom ash, cement/silica fume concretes
(16)	$f_{spt} = 0.31f_c^{0.71}$	Kim at al. [13]	$2.2 \leqslant f_c \leqslant 51.3$; 10–50 °C curing temperature; proposed for Type I, Type V, and Type V/Fly ash concretes
(17)	$f_{spt} = \frac{f_c}{20-\sqrt{FRI}} + 0.7 + \sqrt{FRI}$	Ashour et al. [14]	Proposed for steel fiber reinforced concrete; FRI is the fiber reinforcement index
(18)	$f_{spt} = 0.21f_c^{0.83}$	Xu and Shi [15]	Proposed for steel fiber reinforced concrete

improves the tensile strength, while slightly decreasing the compressive strength.

Soft computing methods have been widely applied to evaluate and predict the properties of concrete such as compressive strength [16–24], modulus of elasticity [25,26], splitting tensile strength [19,27], water permeability [27], etc. Some of these methods include classification and regression trees (CART) [28–30], artificial neural network (ANN) [18,31,32], support vector machine (SVM) algorithms [28,29], and adaptive network-based fuzzy inference systems (ANFIS) [33,34]. Chou et al. [35] compared the performance of ANN, SVM, multiple additive regression tree (MART) and bagging regression tree (BRG) methods to predict the compressive strength of concrete. The results of their study indicated that the ANN and SVM provided the best prediction power for future unseen data. In another research, Chou et al. [28] used SVM, ANN, CART, multilayer perception (MLP), linear regression (LR), and ensemble techniques to predict the compressive strength of concrete. The results of their study showed that the best individual learning methods were SVM and MLP. Recent study by Behnood et al. [25] have used M5′ model tree to predict the modulus of elasticity of recycled aggregate concrete.

Due to the imperfect description of complex physical phenomena using mathematical regression models, some researchers have developed the prediction models of f_{spt} by using machine learning (ML) techniques. Saridemir [36] used gene expression programming (GEP) to develop a model that can predict the f_{spt} of concretes from its f_c and age. Yan et al. [37] utilized support vector machine (SVM) method to predict the tensile strength (f_{spt}) of concrete from its respective compressive strength (f_c).

In this paper, mathematical regression analysis, artificial neural network (ANN), support vector machine (SVM), and M5′ model tree (MT) were applied to predict the tensile strength (f_{spt}) of concretes with and without steel fiber reinforcement. The dataset for this study were extracted from available references. The performance of machine learning techniques, which were used in this study, was compared to each other and with the previously-developed equations by using various measures of prediction accuracy.

2. Methodology

This section describes the statistical and machine learning approaches that were used in the current study to evaluate the splitting tensile strength of concretes made with and without steel fiber reinforcement. These approaches including non-linear regression, artificial neural network (ANN), support vector machine (SVM), and M5′ model tree (MT).

2.1. Non-linear regression

Non-linear regression is a form of regression analysis in which a non-liner combination of the model parameters is used to relate a response variable to a vector of predictor variables. A general form of non-linear regression is given as:

$$Y_i = f(x_i, \theta) + \varepsilon_i \quad i = 1, 2, \ldots, n \tag{19}$$

where Y_i is the responses, f is a known function of the covariate vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{ik})^T$ and the parameter vector $\theta = (\theta_1, \theta_2, \ldots, \theta_p)^T$, and ε_i is random error. The error term is usually assumed to be independent and normally distributed with zero mean and constant variance.

In this study, a logarithmic transformation of multiple linear regression as a function for non-linear problems was used to develop a model which predicts the tensile strength (f_{spt}) of concrete. A general linear regression model and its logarithmic transformation; are presented in Eqs. (20) and (21), respectively.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{20}$$

$$Log(Y) = Log(\beta_0) + \beta_1 Log(X_1) + \beta_2 Log(X_2) + \ldots + \beta_n Log(X_n) \tag{21}$$

where Y is the response variable, β_i is a vector of estimable parameter, and x_i is covariate vector as described previously.

By taking antilogarithms of Eq. (21), it can be transformed into Eq. (22) to evaluate the dependent variable Y.

$$Y = \beta_0 * X_1^{\beta_1} X_2^{\beta_2} \ldots X_n^{\beta_n} \tag{22}$$

In engineering problems, variables are usually dependent on several independent variables. The so-called multivariable power function (Eq. (22)) can be used to successfully characterize this functional dependency and to yield a more realistic result [38].

One of the disadvantages of the regression-based method is the normality assumption associated with this approach that may not be true, especially for wide range of variables. Soft computing methods such as ANN and SVM do not have normality assumption. With a tree classification approach, data sets are classified into more closely related subsets, which helps the regression-based approach to better meet the normality assumption.