Automation in Construction 64 (2016) 7–19

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

# Prediction of self-compacting concrete elastic modulus using two symbolic regression techniques

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ARTICLE INFO

*Article history:*
Received 21 August 2015
Received in revised form 21 December 2015
Accepted 29 December 2015
Available online 14 January 2016

*Keywords:*
Self- compacting concrete
Elastic modulus
Symbolic regression
Artificial bee colony programming
Biogeographical-based programming

ABSTRACT

This paper introduces a novel symbolic regression approach, namely biogeographical-based programming (BBP), for the prediction of elastic modulus of self-compacting concrete (SCC). The BBP model was constructed directly from a comprehensive dataset of experimental results of SCC available in the literature. For comparison purposes, another new symbolic regression model, namely artificial bee colony programming (ABCP), was also developed. Furthermore, several available formulas for predicting the elastic modulus of SCC were assessed using the collected database.

The results show that the proposed BBP model provides slightly closer results to experiments than ABCP model and existing available formulas. A sensitivity analysis of BBP parameters also shows that the prediction by BBP model improves with the increase of habitat size, colony size, and maximum tree depth. In addition, among all considered empirical and design code equations, Leemann and Hoffmann and ACI 318-08's equations exhibit a reasonable performance but Persson and Felekoglu et al.'s equations are highly inaccurate for the prediction of SCC elastic modulus.



## 1. Introduction

Self-compacting concrete (SCC), initially proposed by Okamura in 1986, has gained a wide acceptance in the construction industry [1–3]. SCC is characterized by the ability to flow under its own weight to adequately fill the formwork without any internal or external mechanical vibration [4,5]. SCC also possesses enough viscosity to be handled without segregation or bleeding [6–9].

SCC mixtures are usually designed with limiting aggregate contents, high volumes of paste, a low water–powder ratio, large quantities of mineral fillers, and high range water reducing admixtures [10]. Consequently, the fresh and hardened properties of SCC are different from normally vibrated concrete (NVC) [11]. Several researchers have investigated SCC mix design [12], fresh and hardened properties of SCC [13], and structural performance of SCC members [14]. Due to the rapid growth of the use of SCC, determination of its mechanical properties compared with conventional concrete is essential in order to fulfill design requirements and codes. Elastic modulus of concrete is a crucial mechanical property in design and analysis of concrete structures, for example, member deflections for serviceability requirements, seismic analysis, drift calculations, elastic shortening of concrete in prestressed concrete design, and creep losses [11]. Various relationships were proposed for predicting the elastic modulus of SCC and NVC, mostly from concrete compressive strength [13,15–21].

Various researchers applied different branches of artificial intelligence for predicting the elastic modulus of different types of concrete. Demir [22,23] applied artificial neural network and fuzzy modeling for predicting the elastic modulus of both normal and high-strength concrete. Demir and Korkmas [24] presented a new approach for predicting the upper and lower bounds of elastic modulus of high-strength concrete using fuzzy models. Yan and Shi [25] investigated the use of support vector machine (SVM) to predict the elastic modulus of normal and high-strength concretes from their compressive strengths. Ahmadi-Nedushan [26] applied an adaptive network-based fuzzy inference system (ANFIS) to predict the elastic modulus of normal and high-strength concrete.

Symbolic regression, namely symbolic function identification, is a function discovery approach for analysis and modeling of numeric multivariate datasets. Unlike traditional linear and nonlinear regression methods that fit parameters to an equation of a given form, symbolic regression tries to form mathematical equations by searching the parameters and the form of equations [27,28]. In other words, symbolic regression method searches nonlinear equation forms and its parameters simultaneously for an addressed modeling problem. It attempts to derive a mathematical function to describe the relationship between dependent and independent variables [28,29]. Different novel methods have been developed for symbolic function identification as briefly reviewed in the next paragraph.

In recent years, a variety of evolutionary algorithms (EA) have been developed as feasible and effective methods for optimization problems [30–35]. Many EAs have been proposed, including genetic algorithms (GA), evolution strategies (ES), ant colony optimization (ACO), particle

http://dx.doi.org/10.1016/j.autcon.2015.12.026
0926-5805/

1. Generate initial computer programs ($X_i$) with Ramped half-and-half method
2. Evaluate the computer programs
3. Set cycle to 1
4. **Repeat**
5. **For** each employed bee {
   Produce new computer programs $v_i$ by using information sharing mechanism
   Evaluate the computer programs by using Eqs. (1) and (5)
   Apply greedy selection process between $x_i$ and $v_i$}
6. Calculate the probability values $p_i$ for computer programs by Eq. (2)
7. **For** each onlooker bee {
   Select a computer program $x_i$ depending on $p_i$ probabilistically.
   Produce new computer program $v_i$ by using information sharing mechanism
   Evaluate the computer programs by using Eqs. (1) and (5)
   Apply greedy selection process between $x_i$ and $v_i$}
8. **If** there is an abandoned computer program
   **then** replace it with a new computer program generated by grow method by a scout
9. Memorize the best solution so far
10. cycle = cycle + 1
11. **until** cycle = maximum cycle number

**Fig. 1.** The pseudo-code of the basic ABCP [28].

swarm optimization (PSO), differential evolution (DE), estimation of distribution algorithms (EDA), immune system optimization, artificial bee colony optimization (ABCO), and many others [36]. Inspired by GA, genetic programming (GP), developed by Koza [37], is the most popular technique used in symbolic regression. Afterwards, some researchers introduced different improved versions of genetic programming, for example, linear genetic programming [38], cartesian genetic programming [39], and gene expression programming [40]. However, few researches on using other evolutionary-based algorithms in symbolic regression or automatic programming were also developed. Musilek et al. [41] described immune programming (IP), inspired from the vertebrate immune system, as a paradigm in the field of evolutionary computing. Based on ant colony optimization (ACO) and using dynamically changing pheromone table, Shirakawa et al. [42] proposed dynamic ant programming (DAP) for automatic construction of programs. Gan et al. [43] developed clone selection programming (CSP) for symbolic regression and applied clone selection principle as a search strategy. Inspired by artificial bee colony optimization (ABCO) algorithm, Karaboga et al. [28] introduced artificial bee colony programming (ABCP) as a new symbolic regression method and compared its performance with genetic programming (GP) approach on a large set of symbolic regression benchmark problems. They concluded that ABCP is very

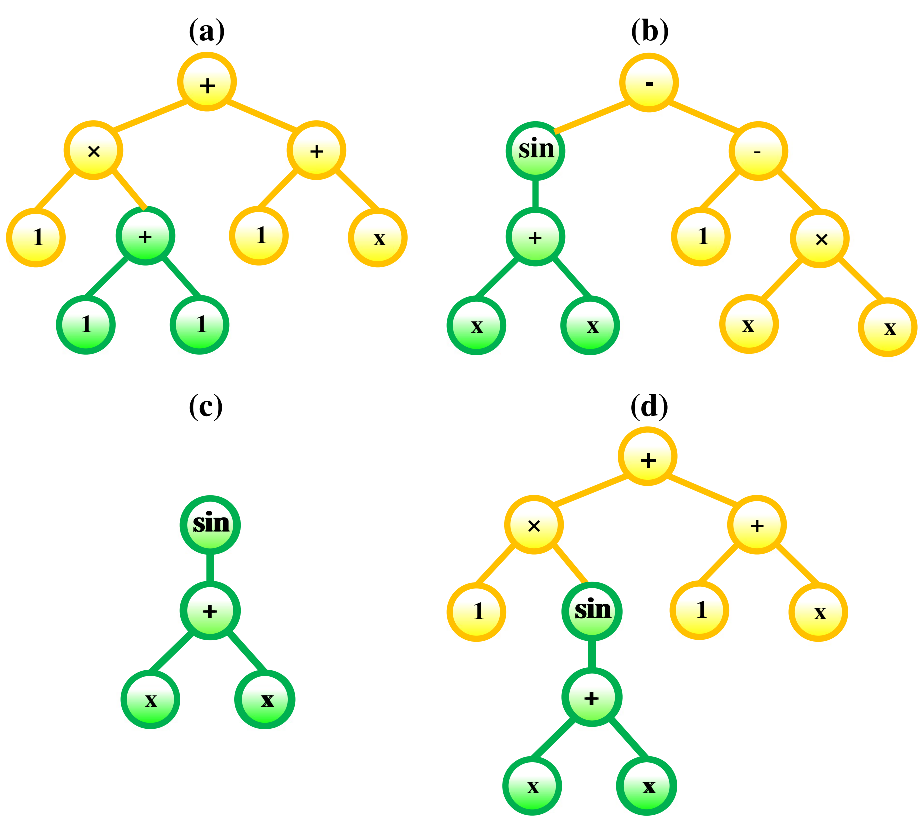


**Fig. 2.** The sharing example of ABCP [28].