***Multiagent Systems for the prediction of Compressive Strength of High performance concrete***  
  
Abstract

Properties of concrete for specific applications depend upon a large sort of factors from mix design to the sort of applied loads. Definitely, the main aspect of using concrete specimens is the mix design. Ranges in constituent materials and mixture proportions of concrete make the procedure of selection hard. Additionally, it's not warranted that the chosen mix design procedure is the best among the considered mixtures. Multi-agent systems (MASs) are a brand new and promising area within the field of distributed computer science (DAI), also as within the mainstream technology. These systems are compound of relatively autonomous and intelligent parts, called agents. Agent-oriented programming languages are programming languages developed for programming of agents. Agent-oriented programming (AOP) can even be seen as a post-object-oriented paradigm. A plus of the usage of agents in software development rather than objects stems from the primitives used for programming [1]. Further, many artificial intelligence-based techniques are conducted to predict compressive strength of concrete specimens. Modified models by metaheuristic optimization algorithms [4] to present approaches with higher performance is also of interest group. The thought is that the agent oriented programming will be employed to predict compressive strength of concrete. Data will be collected from the literature for modelling [8]. It had been suggested that hybrid models [4] are often appropriately used for modelling compressive strength of concrete specimens

Key Words: multi-agents, High performance concrete, Agent-oriented programming, distributed computer science

Introduction

The compressive strength of concrete is determined in batching plant laboratories for every batch in order to maintain the desired quality of concrete during casting. The strength of concrete is required to calculate the strength of the members. Concrete specimens are a cast and tested under the action of compressive loads to determine the strength of concrete.

In very simple words, compressive strength is calculated by dividing the failure load with the area of application of load, usually after 28 days of curing. The strength of concrete is controlled by the [proportioning](https://civildigital.com/various-strands-mix-designing-significance-specific-principles/) of cement, coarse and fine aggregates, water, and various [admixtures](https://civildigital.com/admixtures-in-concrete/). The ratio of the water to cement is the chief factor for determining concrete strength. The lower the water-cement ratio, the higher is the compressive strength.  
  
However we can have simulations done well beforehand to actually know using some permutations and models, is there any way we can computationally increase the strength.

In our approach, a datasets from various geopolymer mixtures including paste, mortar and concrete will collected from the literature [8, 9, 10]. Independent input parameters including content of fly ash, slag, coarse aggregate, fine aggregate, water, superplasticizer, sodium silicate, sodium hydroxide (NaOH) and potassium hydroxide (KOH), oven curing temperature, oven curing time and age of ambient temperature curing will used. Compressive strength will considered as the output parameter. In the authors recent study, it was concluded that the type of fly ash strongly effect on properties of geopolymers. Several types of components of concrete will be considered. According to literature [4] even with a high quality fly ash, mixture proportions and curing conditions must be adjusted well to achieve a geopolymer with high performance. Therefore, the results of this study can be used for optimizing mixture proportions and curing conditions.

Literature Review

As already discussed earlier, properties of concrete for specific applications depend on a wide variety of factors and the main aspect of using concrete specimens being mix design. Ranges in constituent materials and mixture proportions of concrete make the selection procedure hard. Additionally, it is not warranted that the selected mix design procedure is the best among the considered mixtures. Optimization by artificial intelligence (AI) tools may be one of the appropriate methods for mix design of concrete specimens. Application of metaheuristic algorithms such as genetic algorithm (GA) [8-14] and particle swarm optimization algorithm (PSOA) [15] to evaluate different properties of concrete mixtures has been reported widely in the literature. Yuan et al. [8] successfully predicted the compressive strength of concrete by using a hybrid GA-artificial neural networks (ANNs) model, where GA was applied to optimize the weights and thresholds of back-propagation algorithm. In the Tsai’s proposed weighted operation structures (WOS) [9], GA was used to determine selection of functions and proper weights by programming three kinds of concrete-typed specimen strengths including concrete compressive strength, deep beam shear strength, and squat wall shear strength. Lim et al. [10] used GA to optimize mix design of concrete. Several concrete mixtures were examined experimentally and were divided into high and normal strength specimens. The relation between compressive strength (and slump) and input parameters including water to binder ratio, water content, fine aggregate ratio, fly ash replacement ratio, silica fume replacement ratio, air-entraining agent content, and superplasticizer content was achieved by genetic programming (GP). The results indicated that GA is capable to optimize the mix design for the considered concrete specimens in both normal and high strength ranges. Lee et al. [11] used GA to perform the discrete optimization of reinforced concrete plane frames subject to combinations of gravity and lateral loads. Camp et al. [12] employed GA for discrete optimization of reinforced concrete frames to minimize the material and construction costs of the elements subject to serviceability and strength requirements which are described by the American Concrete Institute (ACI) code. Cheng et al. [13] utilized GA to optimize the input parameters of their proposed evolutionary support vector machine (SVM) model consisting of 1030 different concrete mixtures. Tsai [14] used centre-unified particle swarm optimization (CUPSO) approach to optimize the strength in concrete cylinders, reinforced-concrete deep beams and reinforced-concrete squat walls, which had been predicted by hybrid multilayer perceptron (HMLP) networks. Gilan et al. [15] developed a hybrid support vector regression (SVR) –PSOA model to predict the compressive strength and rapid chloride penetration test results of concrete specimens, where PSOA was exploited to optimize the hyper-parameters for SVR. Jayaram et al. [16] used PSOA for design of high volume fly ash concrete mixes including cement content, fly ash content, and water content to maximize the 28-day compressive strength of concrete specimens. Cheng et al. [17] proposed an optimization method based on PSOA to determine 3 thermophysical properties of phase change material (PCM)-concrete bricks. Fonna et al. [18] proposed inverse analysis by minimizing the cost function using PSOA for detecting the corrosion of reinforcing steel in concrete from a relatively small number of potential data measured on the concrete surface. Ahmadi-Nedushan and Varaee proposed [19] a hybrid multi-stage dynamic penalty-PSOA algorithm to solve the constrained cost optimization problem of one-way concrete slabs. Although GA and PSO have shown their performance in optimization of engineering problems dealing with concrete specimens and structures, developing other algorithms more, to obtain higher performance, may be of interest. Ant colony optimization algorithm (ACOA), artificial bee colony optimization algorithm (ABCOA) and imperialist competitive optimization algorithm (ICOA), computational method used to solve optimization problems, may be considered as competitive methods by GA and PSOA. The ant system was introduced by Dorigo et al. [20] and is a relatively new iterative search algorithm for science and engineering problems. It has been inspired by real ant colonies, where in a systematic collaboration ants look for the shortest path they efficiently find from their nest to a food source [21].

Through ACOA, an indirect form of memory of the performance of previously generated solutions is uniquely exploited. ABCOA belongs to the class of stochastic swarm optimization methods inspired by the foraging habits of bees in nature. The artificial bee colony is partially alike to the colonies in nature; however, some differences exist. In ABCOA, configuration of the collective intelligence of the social insect colonies is done by contribution of the communication systems between individual insects. ABCOA’s basic idea is to create a colony of artificial bees called a multiagent system, which is capable of successfully solving difficult combinatorial optimization problems [22].

However, there are very limited work on agent oriented programming for computation of compressive strength of concrete. Some of these limited works in relation to civil engineering problems are achievable in Refs. [12]. In our research, agent oriented programming are used to predict compressive strength of geopolymer paste, mortar and concrete containing various mixture proportions. Geopolymers (alkali-activated binders) are produced by alkali activation of an aluminosilicate source such as fly ash, slag or metakaolin. These eco-friendly cement-free construction materials with lower greenhouse gases emissions are considered as the most probable constituent materials for ordinary Portland cement (OPC). Some evidence of their applications in construction can be found in some bridges and pavements of Victoria (especially in Melbourne), Australia. Although it is used in the same way of OPC to make paste, mortar or concrete, geopolymer binders are normally produced after an oven curing procedure. Therefore, the main factors determine properties of geopolymers are mix design and curing conditions. The required data for modelling purposes of this paper are collected from the literature. The collected data [23] are trained and tested by hybrid GA-SVM, PSOA-SVM, ACOA-SVM, ABCOA-SVM and ICOA-SVM models, where metaheuristic algorithms are used to optimize SVM parameters. The results are compared by simple (non-optimized) SVM, ANNs and ANFIS models.

Research Plan

A model will be developed for estimation of concrete material properties. Data will collected from the literature and arranged as datasets with several inputs and one output parameter. Content of ash, slag, coarse aggregate, fine aggregate, water, superplasticizer, sodium silicate, caustic soda (NaOH) and potassium hydroxide (KOH), oven curing temperature, oven curing time and age of ambient temperature curing, etc are taken as input parameters and compressive strength will the output parameter. Its effectiveness are compared with two other widely-used NN/ML models. The model was tested using concrete test data from the ML repository of the UCI. An ML-optimization model are developed for practical concrete mix design through adroit integration of a nonlinear iterative OA and a computational intelligence-based CA employed in each iteration of OA as a virtual lab to predict whether desired constraints are satisfied or not. The foremost cost effective solutions will be projected. The price savings for large-scale concrete projects will be within the various dollars. Further, the ML model may be developed for global health monitoring of huge structures like highrise building structures through integration of two signal processing techniques, FFT and SWT and two ML algorithms. The model will also be validated using the information obtained from literature. [9]

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