Estimation of Compressive Strength of Geopolymer Mortars using Nature Inspired Algorithm

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Abstract : In this paper, we propose novel nature inspired meta herustic optimization i.e., particle swarm optimization (PSO) to predict the 28-day compressive strength of geopolymer mortars. To construct and validate these models, 81 different mixes with 243 specimens were casted and tested. Seven input parameters were used to predict the tested compressive strength of geopolymer mortars, i.e., the sodium solution (NaOH) concentration (varied as 8M, 11M and 14 M), the mass ratio of alkaline activation solution to precursor content, variation of precursors and their contents, Na/Al ratio and Si/Al ratio . The compressive strength of the fabricated geopolymer mortars was used as output parameter for the prediction models. Validation of the models was done using several criteria's such as variation of inertia weight and incorporating damping coefficient.

The results show that the PSO models have strong potential for predicting the 28-day compressive strength of geopolymer mortars. This study will help in reducing the time and cost for the implementation of laboratory experiments in designing the optimum proportions of geopolymer specimens.

***IndexTerms* – Alkali-activation, PSO, Optimization, compressive strength.**

I. Introduction

In recent decades, novel materials were the subject of widespread research in order to reduce greenhouse emissions in civil engineering activities. Since its invention, geopolymer concrete (GPC) received considerable attention from researchers as an alternative for concrete using ordinary Portland cement (OPC) (Davidovits, 1991). Geopolymer binder is made from two main compounds: (i) rich alumino-silicate materials such as meta-kaolin, fly ash, silica fume, slag, or red mud, and (ii) an activator of alkaline solutions such as sodium or potassium hydroxide and sodium or potassium silicate. Manufacturing OPC generally uses raw materials and releases carbon dioxide, whereas geopolymer binder uses waste by-product materials. Therefore, such green materials are an excellent alternative for sustainable development.

Artificial Intelligence methods have been extensively used in the fields of civil engineering applications e.g. construction management, building materials, hydraulic optimization, geotechnical and transportation engineering and newly added EHS. Over the past 20 years, in the civil engineering field, development and application of the expert system have made a lot of achievements, mainly used in project evaluation, diagnosis, decision-making and prediction, building design and optimization, the project management construction technology , road and bridge health detection and some special field, and so forth. Among AI based computational techniques, adaptive neuro-fuzzy inference systems were particularly suitable for modelling complex systems with known input-output data sets especially to study the behaviour of cement-based materials undergoing single, dual, or multiple damage factors. The model allows construction planners to generate and evaluate optimal/near-optimal construction scheduling plans that minimize both project time and cost. AI also helps in development of robots and automated systems. Even the role of artificial intelligence is also reported in the case of smart materials. The smart system refers to a device which can sense changes in its environment and can make an optimal response by changing its material properties, geometry, mechanical or electromagnetic response. Both the sensor and the actuator functions with their appropriate feedback must be properly integrated (Lazarevska, et al. 2012; Lazarevska et al. 2014).

II. Meachine Learning Methods

2.1 Fuzzy Logic

A superset of Boolean logic dealing with the concept of partial truth -- truth values between "completely true" and "completely false". It was introduced by Dr. Lotfi Zadeh of UCB in the 1960's as a means to model the uncertainty of natural language. Any specific theory may be generalized from a discrete (or "crisp") form to a continuous (fuzzy) form, e.g. "fuzzy calculus", "fuzzy differential equations" etc. Fuzzy logic replaces Boolean truth values with degrees of 5 truths which are very similar to probabilities except that they need not sum to one. Instead of an assertion pred(X), meaning that X definitely has the property associated with predicate "pred", we have a truth function truth (pred(X)) which gives the degree of truth that X has that property.

2.2 Neural Networks

A network of many very simple processors ("units" or "neurons"), each possibly having a (small amount of) local memory. The units are connected by unidirectional communication channels ("connections"), which carry numeric (as opposed to symbolic) data. The units operate only on their local data and on the inputs they receive via the connections. A neural network (NN) is a processing device, either an algorithm, or actual hardware, whose design was inspired by the design and functioning of animal brains and components thereof. Most neural networks have some sort of "training" rule whereby the weights of connections are adjusted on the basis of presented patterns. In other words, neural networks "learn" from examples, just like children learn to recognize dogs from examples of dogs, and exhibit some structural capability for generalization. Neurons are often elementary non-linear signal processors (in the limit they are simple threshold discriminators). Another feature of NNs which distinguishes them from other computing devices is a high degree of interconnection which allows a high degree of parallelism. Further, there is no idle memory containing data and programs, but rather each neuron is pre-programmed and continuously active.

2.3 Evolutionary Algorithm

Genetic Algorithm (GA) An evolutionary algorithm which generates each individual from some encoded form known as a "chromosome" or "genome". Chromosomes are combined or mutated to breed new individuals. "Crossover", the kind of recombination of chromosomes found in sexual reproduction in nature, is often also used in GAs. Here, an offspring's chromosome is created by joining segments chosen alternately from each of two parents' chromosomes which are of fixed length. GAs are useful for multidimensional optimization problems in which the chromosome can encode the values for the different variables being optimized.

2.4 Application of Artificial Intelligence in Concrete

Concrete compressive strength (CCS) is usually predicted using linear or non-linear regression methods (Bharat et al. 2001; Bhanja and Sengupta, 2002; Atici, 2010; Zain and Abd, 2009). The general form of the regression method is where y, f, bi and xi are the CCS, linear or nonlinear function, regression coefficients and concrete attributes, respectively. However, obtaining an accurate regression equation when using these empirical-based models is difficult. Moreover, several factors that affect the compressive strength of HPC differ from those that affect the compressive strength of conventional concrete. Therefore, regression analysis may be unsuitable for predicting
CCS (Yeh and Lien, 2009).

To compensate for the drawbacks of conventional models, machine learning algorithms (i.e., neural networks, classification and regression tree, linear regression, or support vector machine (SVM)) as baseline models have been applied in evolutionary or hybrid approaches to developing accurate and effective models for predicting CCS. Recently, the use of ML-based applications has increased in many areas of civil engineering, ranging from engineering design to project planning (Topcu and Sandemir, 2008). Other material science problems that have been solved by ML include mixture design, predicting mechanical properties, or fault diagnosis (Cheng et al. 2012; Peng et al. 2010; Gupt, 2007).

III. Experimental Investigation

The materials used in the experimental investigation were i) Ennor sand, (ii) Ground granulated blast furnace slag (GGBS), (iii) Rice husk ash (RHA), (iv) Silica fume and (v) Alkali activated solution, which is a mixture of sodium silicate gel (Na_2SiO_3) and sodium hydroxide pallets (NaOH). In this study the NaOH concentration molarity (M) was varied as 7M, 11M and 14M. The ratio of Na_2SiO_3/NaOH maintained as 2.5.The compressive strength of geo-polymer concrete is examined for the mixes of varying molarities of Sodium hydroxide (8M, 11M and 14M). The molecular weight of sodium hydroxide is 40. To prepare 14M i.e. 14 molar sodium hydroxide solution, 560g of sodium hydroxide flakes are weighed and they can be dissolved in distilled water to form 1 liter solution. For this, volumetric flask of 1 liter capacity is taken, sodium hydroxide flakes are added slowly to distilled water to prepare 1liter solution.

The conventional method used in the making of normal concrete is adopted to prepare geo-polymer mortar. First, the ennor sand, GGBS and silica fume are mixed in dry condition for 3-4 minutes as aforementioned proportions and then the alkaline solution which is a combination of Sodium hydroxide solution and Sodium silicate solution is added to the dry mix. The mixing is done about 6-8 minutes for proper bonding of all the materials. After the mixing, the cubes are casted with the mixes A1 to A9 by giving proper compaction. The sizes of the cubes used are of size 75mmX75mmX75mm.

The compressive strength of all the mixes was examined at the age of 28 days ambient curing and also for 30mins, 1hour, 7hours and 24hours in oven curing by maintain temperature 105^{o}C or the various replacement levels of precursors contents and prepared with different molarity of alkaline activator. the values of average compressive strength for different replacement levels of precursors such as GGBS, silica fume and rice husk ash (as mentioned in Chapter-IV) and prepared with different concentration of alkaline activator (8M,11M and 14M).

IV. RESULTS AND DISCUSSION

For developing prediction models by using input variables as sodium solution (NaOH) concentration (varied as 8M, 11M and 14 M), the mass ratio of alkaline activation solution to precursor content, variation of precursors and their contents, Na/Al ratio and Si/Al ratio.

The data information of sodium solution (NaOH) concentration (varied as 8M, 11M and 14 M), the mass ratio of alkaline activation solution to precursor content, variation of precursors and their contents, Na/Al ratio and Si/Al ratio are considered as input variables to predict compressive strength of geopolymer mortars. Linear regression models were used to estimate or predict unknown variables with known variables are in vogue. In this project, the multi linear model equations were developed for predicting compressive strength of geopolymer mortars instead of taking direct regression models. For this developed equation, each variable such as RHA content (V1), GGBS content (V2), silica fume content (V3), molarity (V4), alkali solution content (V5), Na/Al and Si/Al was multiplied by respective coefficients such as a_1, a_2, a_3, a_4, a_5, a_6 and a_7 was considered.

Table 1. Test data of the geopolymer mortars

Mixes	V1	V2	V3	V4	V5	V6 (Compressive strength) (N/mm^2)
1	0	100	0	8	16	40
2	0	90	10	8	16	36.85
3	0	160	20	8	16	32.5
4	0	140	30	8	16	30.5
5	0	120	40	8	16	28.5
6	5	180	5	8	16	43.5
7	10	160	10	8	16	36.5
8	15	140	15	8	16	30.5
9	20	120	20	8	16	22.35
10	0	100	0	8	18	42.5

In order to reduce greenhouse emissions in civil engineering activities, many novel construction materials were developed in recent decades. Unlike the fabrication process of OPC using compounds that release carbon dioxide, GPC uses waste by-product materials which are environment friendly, and can be defined as green materials. Mechanical properties of GPC proved that this material can work as effectively as traditional OPC-based materials.

Particle swarm optimization (PSO) models are proposed for predicting the compressive strength of the geopolymer mortars. Basically, the AI algorithm can predict the results which are only in good agreement with the target data, but not better regarding quality and quantity. The below equation was the best trail after taking number trails and changing inertia weights.

$$CS_{(est)} = -0.272.RHA + 0.011.GGBS - 0.369.SF + 2.507.M + 1.803.AS - 2.551.Na/Al + 0.257.Si/Al - 12.515 \quad \text{---(1)}$$

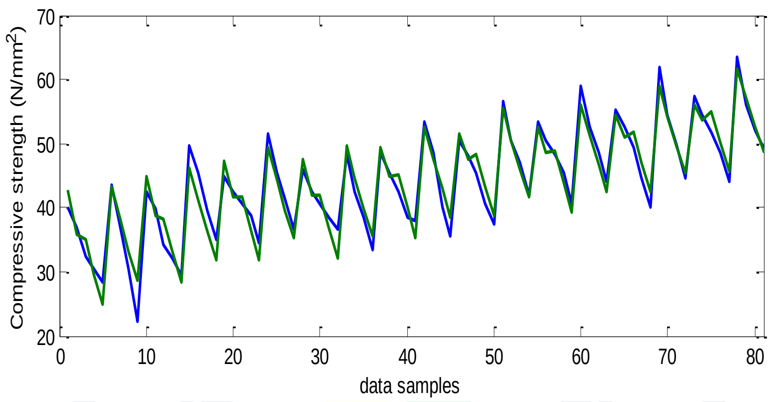

Figure.1 Predicted compressive strength using PSO

Swarm assisted particle multi linear regression model which enables adequately predicts the compressive strength of the geopolymer mortars. Thus, it can be reasonably concluded that the proposed PSO is a promising method for the prediction of the compressive strength of geopolymer mortars. This study would help in reducing the time and cost of construction, as well as in the improvement of the environment. However, a limitation of this study is that we considered only ambient condition, and we did not consider the curing conditions which might affect the compressive strength of geopolymer mortars. Thus, this is proposed to carry out a study of these factors in future modeling.

V. CONCLUSIONS

The following conclusions can be drawn from the foregoing study:

1. Geopolymer concrete or mortars is an eco-environmentally friendly material which can be used as a replacement for cement concrete in civil engineering construction.
2. The compressive strength is an important parameter for evaluation of the quality of this material.
3. In this study, novel hybrid nature inspired swarm assisted algorithm, PSO was proposed for quick prediction of the compressive strength of geopolymer mortars. A total of 140 samples were generated having 25 mixes and tested in the laboratory to determine the parameters for modeling, such as the compressive strength as the output variable, and RHA content (RHA), GGBS content (GGBS), silica fume content (SF), molarity (M), alkali solution content (AC), Na/Al and Si/Al were considered as input variables.
4. The results show that the proposed models performed well for the prediction of the compressive strength of geopolymer mortars, but the inertia weight selection depends on the best result after conducting various trails.
5. Thus, it can be reasonably concluded that the proposed PSO is a promising method for the prediction of the compressive strength of geopolymer mortars. This study would help in reducing the time and cost of construction, as well as in the improvement of the environment. However, a limitation of this study is that we considered only ambient condition, and we did not consider the curing conditions which might affect the compressive strength of geopolymer mortars. Thus, this is proposed to carry out a study of these factors in future modeling.

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