Predicting the strength characteristics of alkali activated concrete with environment friendly precursors using statistical methods

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Abstract. Over the recent twenty years, utilization of ordinary Portland cement (OPC) has expanded dramatically, making it the world’s most mass-produced product. OPC manufacture is energy demanding, uses non-renewable naturally available resources, and is a major contributor to global warming (responsible for nearly 8 percent of global CO₂ exhalations). A substitute to OPC concrete (OPCC) is Alkali Activated Concrete (AAC), in which precursors (raw materials) such as Blast Furnace Slag (GGBS), Fly Ash (FA) and other residues are activated with an activator solution. Statistical analysis is preferred for concrete related experiments incorporating a large number of samples and data in order to save time, money and work labour. The current work deals with developing statistical models for anticipating the compressive behaviour of AAC. Regression analysis is performed to determine the significant impact of variables on the compression behaviour and also to develop several linear regression models to predict the compressive strength of AAC at the age of 28 days. In the present work, collection of data base regarding mix proportions and mechanical properties of AAC is done through an extensive literature survey. This study identifies JASP as one of the most effective online tools for generating regression models.

1 Introduction

Conventional Portland cement (OPC) is the most widely employed building material on a global scale, second only to water, with an annual use of one cubic meter per person [1]. Blended concretes are proposed to lessen the reliance on OPC, emphasize the utilization of agro and industrial wastes like Ground Granulated Blast Furnace Slag (GGBS), Fly Ash (FA), Silica Fume (SF), Metakaolin (MK), Rice Husk Ash (RHA), and subsequently curb the carbon dioxide (CO₂) emissions related to its manufacture [2]. Green concretes such as Alkali Activated Concrete (AAC) and Geopolymer Concrete (GPC) are cementless concretes in

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which the binder materials substitute cement [3]. AAC is made up of a solid precursor rich in calcium/alumino silicates, an activator solution and aggregates [4]. GGBS, FA (including Class C and Class F), calcined clays, MK, RHA, volcanic ash, and other alkali-activated binders or concretes have all been extensively researched for alumino silicate and calcium silicate resources. GGBS and FA (Class F) are encouraging binder materials in terms of practicality, in view of the ease with which they can be obtained and their high pursuance as alkali-activated binders. Silicates, hydroxides, and carbonates (typically in slag-occupied systems) are the common alkaline activators [5-10]. For studies involving the replacement of concrete materials, Design of Experiments (DoE) approaches that employ more advanced methods for analysing experimental data are highly advantageous [11]. In the investigations of replacement materials like tyre rubber [12], palm oil fuel ash [13], and others, various DoE have been utilized. In another scenario, design methods for concrete mixes, frequently involving the incorporation of novel recycled materials, are optimized using artificial intelligence-based techniques [14]. Fasih et al., [15] used an artificial neural network (ANN) to create a predictive model to examine the interaction between rubber and AAC. The equations developed had fine rubber and time as input variables and strength in compression, tension, and bending, water absorption, and carbonation depth as responses. Regression analysis is the easiest technique for determining the relationship between parameters. When estimating the consecutive relationship amongst a predictor and a reference variable, the model is considered as of simple linear regression (SLR), but when predicting a linear relationship among two or more predictors (upto ten) and another reference variable, the model is said to be of multiple regression (MLR). In the study conducted by Olonade et al.,[16], regression with a singular variable, which was concrete age, was utilized to estimate concrete strength under various curing conditions. In all five instances, R2 values ranged from 0.87 to 0.98, demonstrating that the age and compressive strength of concrete exhibit unwavering linearity for varying curing conditions. The equation enabled the researchers to evaluate the efficacy of every variable by contrasting the constant coefficient and the slope, which represented the degree of strength gain. Diaz et al., [17] compared the mechanical conductivity of FA made GPC. The data was analyzed using regression analysis to find patterns and correlations in GPC's mechanical properties. The mechanical behaviour of GPC was discovered to be identical to that of OPCC. Multiple linear regression (MLR) remains as most basic form of multiple regression and is employed to obtain satisfactory results in numerous studies [18]. MLR models the linearity among all variables and the dependent variable, whereas the influence of some variables could be nonlinear. In certain investigations, the efficacy of MLR can be comparable to many diverse advanced techniques such as ANN [19]. Table 1 displays the summary of regression methods adopted by various researchers. The Taguchi method and Response Surface Methodology (RSM) are opted for experimental investigations incorporating a huge data and a lot of samples in order to simplify the testing of the experiments [20]. Ahmad et al., [21] are aimed at manufacturing AAC by making use of within reach accessible MK and limestone powder (LSP) as constituent materials. Samples with various basic binders and their content, types of activators, and composition of activators were made and examined for strength in compression. The acquired experimental data was subjected to statistical analysis using Response surface methods (RSM) and one way ANOVA for investigating the importance of variables under study. The outcomes of the tests revealed that all the variables considered had a considerable impact on the measured quantities, in which there was a pronounced effect by the primary binder to the alkaline composition. Zhang et al., [22] suggested using machine learning (ML) based on chemical analysis to ascertain the compressive strength of AAM, relying on the AAM mix ratio and the oxide composition of the precursor and activator. Support vector machines, random forests, complementary trees, and gradient boosting are four practical machine learning models that have had their prediction performance enhanced through chemistry-
based feature engineering. An average error of 3.228 MPa was used to make the correct prediction. Extensive tests were performed employing the most effective prediction model to ascertain influence of various mixed variables on the growth of AAM compressive strength. Correspondingly, the impact of the precursor and activator composition on compressive strength has received substantial research, and the findings have been carefully examined. It is evident that statistical assessment is beneficial for concrete material investigations and that sophisticated statistical methods such as Jeffreys’s Amazing Statistics Program (JASP) could be more reliable for modelling analyses involving more variables. JASP is a publicly available application supported by University of Amsterdam. It provides simple user-friendly interface and is much acquainted to SPSS (Statistical Package for the Social Sciences) customers as well. JASP 0.8.5.1 version has been used in this work. Figure 1 shows the homepage of JASP 0.8.5.1 version used for this work. The current work deals with developing statistical predictive models for determining the compressive strength behaviour of AAC. Regression analysis is performed to determine the remarkable influence of variables on the compression behaviour and also to develop several linear regression models to predict the compressive Strength of AAC at the age of 28 days.

Table 1. Summary of regression methods adopted by various researchers

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Number of independent variables</th>
<th>Regression method</th>
<th>$R^2$</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compressive strength</td>
<td>1</td>
<td>SLR</td>
<td>0.89</td>
<td>[20]</td>
</tr>
<tr>
<td>Compressive strength</td>
<td>1</td>
<td>SLR</td>
<td>0.87-0.96</td>
<td>[23]</td>
</tr>
<tr>
<td>Compressive strength</td>
<td>1</td>
<td>SLR</td>
<td>0.87-0.98</td>
<td>[16]</td>
</tr>
<tr>
<td>Compressive strength</td>
<td>5</td>
<td>MLR</td>
<td>0.82</td>
<td>[24]</td>
</tr>
<tr>
<td>Compressive strength</td>
<td>7</td>
<td>MLR</td>
<td>0.96-0.98</td>
<td>[25]</td>
</tr>
<tr>
<td>Compressive strength</td>
<td>8</td>
<td>MLR</td>
<td>0.8</td>
<td>[26]</td>
</tr>
</tbody>
</table>
2 Materials and Methods

Data samples with FA and GGBS as solid precursors, alkaline activator solution consisting of an amalgamation of sodium hydroxide (SH) and sodium silicate (SS) are used. The experimental data used for the analysis is inferred from 49 reputed journals that used FA, GGBS, SS and SH as activator from which a total of 400 data points are extracted. Traditional SLR and MLR are adopted in JASP for suggesting linear correlation amongst the independent and dependent variables. The R-Squared value thus obtained helps in determining the amount through which an unbiased variable motion can be explained from a structured variable. Table 2 emphasizes the selection of both dependent and independent variables adopted in this work and the combinations for which models have been proposed.

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Dependent variable</th>
<th>Combinations</th>
</tr>
</thead>
<tbody>
<tr>
<td>FA, GGBS, Activator Solution</td>
<td>Compressive strength</td>
<td>GGBS content Vs Compressive strength</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Activator solution Vs Compressive strength</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FA + Activator solution Vs Compressive strength</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GGBS + Activator solution Vs Compressive strength</td>
</tr>
<tr>
<td></td>
<td></td>
<td>FA+ GGBS content + Activator solution Vs Compressive strength</td>
</tr>
</tbody>
</table>
3 Results and Discussions

3.1 Correlation analysis

The degree of connection of two variables is measured by correlation analysis. We can calculate the correlation coefficient, which shows us how much one variable change when the other changes, using correlation analysis. It also shows a linear relationship between two variables. To run the correlation analysis in JASP, go to the top bar -> Click Regression -> Correlation matrix -> Choose the two variables. We can also obtain a correlation plot amongst the two variables chosen as shown in Figure 2 and Figure 3. A positive direct correlation coefficient indicates that a rise within the first variable would correspond to a rise within the second variable thus implying an immediate relationship between variables [27].

The correlation of FA and GGBS with 28-day compressive behaviour of AAC was positive indicating the increment in strength with an increase in percentage of FA. FA can be replaced up to 50% of the binder in concrete, reducing OPCC strength. In addition, FA incorporation makes concrete more impermeable due to micro filling effect of it [28]. The compressive quality of concrete blends containing GGBS increases with the amount of increment of the GGBS. The incorporation of GGBS doesn’t show any progress in the compressive behaviour of concrete after 55% replacement of cement with binder for OPC. This can be clarified by the existence of nonreacted GGBS left in the paste [29]. Variables which are negatively correlated have the opposite relationship. A negative correlation can be observed between alkaline solution and compressive strength indicating that the increase in quantity of activator solution decreases the compressive strength. Porosity of the paste increases with increase in Solution to Binder (S/B) ratio, thereby reducing the dense nature of the concrete and hence results in a poor microstructure [30]. With increase in S/B ratio, the drying shrinkage of the geopolymer paste increases and hence more microcracks form in the hardened paste [31].

Fig. 2. Correlation analysis in JASP
3.2 Regression analysis and ANOVA

The outcome of compressive strength as the variable of interest and variables like FA, GGBS, activator solution as independent variables is predicted using SLR and MLR analyses. To perform regression in JASP, go to the top bar -> Click Regression -> Click Linear Regression -> Choose one variable for Dependent Variable and other variables for Covariates (Covariates refer to independent variables). Figure 4 shows the output obtained by performing regression among FA and CS of AAC at the age of 28 days. Both SLR and MLR were used in this research. $R^2$ value of more than 0.8 is obtained for all the combinations demonstrating the capability of model in forecasting the strength in compression of AAC after 28 days [32]. ANOVA is a set of numerical models used to assess variation within and across groups and to analyze differences between them. The p-value obtained from ANOVA helps in measuring the statistical significance of the prediction model. The p-value for each independent term in the model (FA, GGBS, activator solution) was less than 0.05, indicating that they were all significant for the dependent variable (compressive strength). To perform ANOVA in JASP, go to the top bar -> Click ANOVA -> Click ANOVA under Classical section -> Choose one dependent variable for Dependent Variable and grouping variables for fixed factors. The sum of squares and the p-value obtained from ANOVA can be noticed from Figure 5. The AAC statistical model is accurate enough to predict the properties in fresh and hardened state since p-value for all combinations is less than 0.05 [33]. Table 3 outlines the Regression and ANOVA results obtained from this work as follows.
Fig. 4. Regression Output in JASP

Results ▼

Linear Regression ▼

Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R²</th>
<th>Adjusted R²</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.832</td>
<td>0.795</td>
<td>0.785</td>
<td>4.888</td>
</tr>
</tbody>
</table>

ANOVA ▼

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1850.7</td>
<td>1</td>
<td>1850.73</td>
<td>77.46</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Residual</td>
<td>477.8</td>
<td>20</td>
<td>23.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>2328.6</td>
<td>21</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Coefficients

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized</th>
<th>Standard Error</th>
<th>Standardized</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Intercept)</td>
<td>-43.285</td>
<td>8.505</td>
<td>-5.089</td>
<td>&lt; .001</td>
<td></td>
</tr>
<tr>
<td>FLYASH</td>
<td>0.179</td>
<td>0.020</td>
<td>0.892</td>
<td>8.801</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Fig. 5. ANOVA Output in JASP
### Table 3: Entire results of the work

<table>
<thead>
<tr>
<th>Combination</th>
<th>$R^2$</th>
<th>p-value</th>
<th>Variable</th>
<th>Intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>FA Vs CS</td>
<td>0.8</td>
<td>&lt;0.001</td>
<td>0.179</td>
<td>-43.285</td>
</tr>
<tr>
<td>GGBS Vs CS</td>
<td>0.861</td>
<td>&lt;0.001</td>
<td>0.104</td>
<td>2.298</td>
</tr>
<tr>
<td>FA+ GGBS Vs CS</td>
<td>0.812</td>
<td>&lt;0.001</td>
<td>-0.103, 0.062</td>
<td>64.578</td>
</tr>
<tr>
<td>FA+ Activator solution Vs CS</td>
<td>0.886</td>
<td>&lt;0.001</td>
<td>-0.044, -0.513</td>
<td>158.811</td>
</tr>
<tr>
<td>GGBS +Activator solution Vs CS</td>
<td>0.886</td>
<td>&lt;0.001</td>
<td>0.147, 0.105</td>
<td>-24.130</td>
</tr>
<tr>
<td>FA+ GGBS +Activator solution Vs CS</td>
<td>0.810</td>
<td>&lt;0.001</td>
<td>0.076, 0.049</td>
<td>-0.366</td>
</tr>
<tr>
<td>Activator solution Vs CS</td>
<td>0.81</td>
<td>&lt;0.001</td>
<td>-0.144</td>
<td>72.885</td>
</tr>
</tbody>
</table>

The proposed linear regression models for envisaging the compressive strength of AAC at 28 days are represented by the following Eqs. (1) to (7)

\[
\text{CS} = 0.179 \times \text{FA} - 43.285 \tag{1}
\]

\[
\text{CS} = 0.104 \times \text{GGBS} + 2.298 \tag{2}
\]

\[
\text{CS} = -0.103 \times \text{FA} + 0.062 \times \text{GGBS} + 64.578 \tag{3}
\]

\[
\text{CS} = -0.044 \times \text{FA} - 0.513 \times \text{Activator solution} + 158.811 \tag{4}
\]

\[
\text{CS} = 0.147 \times \text{GGBS} + 0.105 \times \text{Activator solution} - 24.130 \tag{5}
\]

\[
\text{CS} = 0.076 \times (\text{FA} \text{ and } \text{GGBS}) + 0.049 \times \text{Activator solution} - 0.366 \tag{6}
\]

\[
\text{CS} = -0.144 \times \text{Activator solution} + 72.885 \tag{7}
\]

Eqs. (1) and (4) can be successfully employed to geopolymer mixtures for which a suitable alkaline activator with a suitable curing regime are crucial constituents in contributing towards the strength in compression. As a result of its limited reactivity at room temperature, fly ash-based geopolymers must be cured at temperatures above 60 °C and to achieve desirable mechanical properties [34-36]. Consequently, curing at elevated temperatures is a particularly significant factor. However, curing at high temperatures runs against the goal of avoiding Portland cement, which is to cut down on CO$_2$ emissions. This is because curing at high temperatures needs more energy than curing at ambient temperature does. Several investigations have added Calcium oxide (CaO) containing slag to fly ash-based geopolymers to achieve an increment in the compressive strength at ambient temperature. Yip et al., [37] discovered that the chemistry of added Ca$^{2+}$ significantly improves geopolymer mechanical characteristics i.e a single binder can generate geopolymeric and calcium silicate hydrate (CSH) gels. Hence Eqs. (2) and (5) are suitable for adopting them to anticipate the compressive strength of slag-based alkali activated mixes. Temuujin et al., [38] discovered that adding Calcium to FA enhanced greatly the mechanical characteristics of specimens treated under air curing. In geopolymers that are produced from fly ash/slag mixes, ambient curing increased binder strength and reduced system porosity, which could affect strength enhancement and industrial by product use, indicating the employment of Eqs. (3) and (6). From Eq. (7), it is very clearly noticeable that the compressive strength could decline in the alkali-activator content is increased as a consequence of the high shrinkage amount [39].
4 Conclusion

To establish mathematical models for various mix proportions of constituent materials used, JASP has been introduced to predict the 28-day compressive strength properties of AAC. The ANOVA results examine the effect of each variable on the replies, and the following significant conclusions can be drawn:

- The correlation coefficients of independent variables and dependent variables is observed to be excellent (>0.75 for all combinations).
- The adjusted and predicted R² values showed that the prediction models were sufficient to detail the correspondence among input variables and output responses and were fit for optimization.
- The suggested mathematical models can forecast the 28-day compressive strength of AAC and have been found to be significant when utilizing the p-value approach.
- The standard error was observed to be less than 5% for all the combination of independent variables considered there by representing the lying of samples closer to the mean of the population.

References


