Fly Ash in Self-Consolidating Concrete: Performance, Sustainability, and Optimization with Specialized Machine Learning Application

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Abstract— This research explores the impact of incorporating fly ash into self-consolidating concrete (SCC) containing volcanic aggregates, with a focus on improving rheological and mechanical properties for sustainable construction. By examining flowability, resistance to segregation, and compressive strength, the study demonstrates how fly ash enhances both performance and durability in SCC mixes. Furthermore, the integration of machine learning techniques, particularly Additive Regression, has enabled precise prediction of SCC plastic viscosity based on constituent proportions, achieving a high correlation coefficient of 0.9527 and low error metrics (Mean Absolute Error of 1.3337 and Root Mean Squared Error of 1.6925). The findings emphasize the potential of fly ash to not only improve concrete performance but also to support environmental sustainability by enhancing compatibility with liquid CO2 admixtures. This dual benefit positions fly ash as a vital component in the development of carbon-neutral concrete technologies, offering a pathway to more efficient, durable, and eco-friendly construction practices in the modern built environment.

Keywords—Fly ash, Self-consolidating concrete (SCC), Volcanic aggregates, Rheological properties, Mechanical performance, Liquid CO2 admixtures, Sustainable construction.

I. INTRODUCTION

Ancient Roman concrete was frequently praised for its incredible endurance, resisting environmental and structural obstacles for millennia. The secret to its longevity is its distinct composition, notably the use of pozzolana, a volcanic ash, and its unique "hot mixing" method. These components and processes provide Roman concrete self-healing characteristics, allowing constructions to last over the years. For example, pozzolana combines with calcium hydroxide in lime to generate calcium-silicate-hydrate (CSH), which is responsible for the concrete's strength. Meanwhile, the "hot mixing" technique promotes the creation of lime clasts, which react with the intruding water to produce calcium carbonate, closing fissures and restoring structural integrity. Together, these components give Roman concrete remarkable self-healing capabilities, enabling structures to remain intact over centuries. The principles of Roman concrete provide valuable insights into creating modern materials with enhanced durability and sustainability [1,2,3].

Contemporary concrete technology has progressively researched the use of pozzolanic ingredients such as fly ash to reduce the considerable carbon footprint linked to traditional concrete manufacturing. Fly ash is the waste product of coal combustion, yet it enhances concrete's rheological and mechanical properties, and it additionally contributes to environmental sustainability by lowering consumption of Portland cement. Self-consolidating concrete (SCC), is renowned for its high flowability and resistance to segregation, is an excellent choice for adding such supplementary cementitious materials (SCMs). SCC eliminates the need for mechanical compaction, making it highly suitable for complex structural elements [4,5]. Despite the well-documented short-term benefits of SCC, there is still much to explore regarding its long-term performance and its compatibility with a wider range of aggregates and SCMs. Expanding the material scope to include various aggregate types and SCMs is critical to developing concrete mixes with enhanced performance and adaptability to diverse construction needs [6,7,8]

Existing literature has extensively documented the benefits of using fly ash in concrete, including improved workability, reduced heat of hydration, and enhanced long-term strength. Studies have also highlighted its role in mitigating alkali-silica reactions and improving durability in harsh environments. However, there is a lack of research on how combinations of fly ash with alternative aggregates— such as volcanic aggregates—and other SCMs influence SCC's mechanical and rheological properties. Furthermore, few studies have comprehensively investigated the synergistic effects of fly ash and liquid CO2 admixtures on SCC's performance and sustainability. Also, The optimization of SCC mix designs using modern developing algorithms such as machine learning (ML) is a relatively new field of research. While machine learning has been used in a variety of civil engineering domains, its potential to expedite the SCC mix

design process, particularly in predicting crucial characteristics like as plastic viscosity, goes overlooked [9,10,11,12,13] .

This research addresses these gaps by examining the effect of fly ash on the rheological and mechanical characteristics of SCC with volcanic particles. It also investigates the compatibility of fly ash with liquid CO2 admixtures in order to generate carbon-neutral materials for construction. In addition, the study emphasizes on the significance of using a wider variety of aggregates and SCMs to build diverse and high-performance SCC mixtures.

Besides, the research uses machine learning techniques such as additive regression to improve SCC mix designs, resulting in a data-based approach to obtaining desired performance characteristics. The paper provides a new viewpoint on improving the performance and sustainability of SCC in modern building by combining experimental and computational methods.

Fig 1: Engineering Marvels: The Pantheon and the Strength of Pozzolanic Concrete

II. Research Objectives

This study intended to assess the impact of adding fly ash into SCC utilizing volcanic aggregates. It sought to determine how fly ash affects rheological qualities such as flowability and resistance to segregation in SCC. Mechanical tests were carried out to determine the impact of fly ash on its compressive strength, durability, and sustainability. Machine learning algorithms were used to forecast plastic viscosity based on mix proportions, including fly ash concentration, at the same time improving SCC designs. This study also aimed to check the compatibility of liquid CO2 admixtures with fly ash for carbon-neutral, sustainable construction applications.

III. Methodology

The methodology included an in-depth analysis of SCC with volcanic ash to determine its rheological, mechanical, and durability characteristics. Mixtures of SCC were produced using a variety of aggregate sizes, ratios, and water-cement proportions as well as admixtures such as superplasticizers and viscosity modifiers to test their impacts on flow, stability, and segregation. Rheological tests, such as slump flow, visual stability index (VSI), and segregation probe, were used to assess yield stress, plastic viscosity, and overall workability of the mixtures. Collection of data involved testing each SCC combination for fresh and hardened states, as well as durability. Mechanical testing such as compressive and tensile

strength were done in accordance with ASTM guidelines. Machine learning algorithms, such as random forest and gradient boosting, were used to estimate plastic viscosity from constituent proportions.

Moreover, a field test using liquid CO2 admixture is conducted to assess its potential for reducing carbon emissions in concrete, with estimations of the impact on fresh and hardened properties, as well as long-term durability. More details can be found in [14].
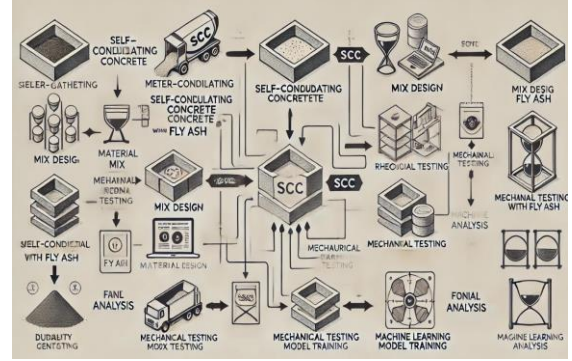

Fig 2: Flow Chart Diagram

IV. Machine Learning Models

A. Multilayer Perceptron

One of the artificial neural networks in deep learning is the Multilayer Perceptron (MLP). Here, data flows in one direction from input to output justifying its feedforward structure. MLP includes neurons (consists of multiple layers of interconnected nodes, these are structured in three main parts: an input layer, one or more hidden layers, and an output layer.). Each connection between nodes carries a specific weight, and each node applies an activation function to its input, enabling the network to learn and make complex decisions.

MLPs are widely valued for their ability to learn non-linear relationships, making them highly effective in diverse tasks such as classification, regression, and pattern recognition. They play a critical role in applications like image and speech recognition, natural language processing, medical diagnostics, and even financial market prediction, where identifying complex patterns and trends is essential for accurate predictions [15, 16].

B. Random Committee

In WEKA program, the Random Committee is an ensemble learning method used to improve the robustness and accuracy of predictive models. It leverages multiple instances of a base classifier, each trained on the entire dataset but with slight variations introduced through randomization. This ensemble of classifiers collaborates to provide a single, averaged prediction, which often results in improved performance compared to a single classifier. The core idea is to reduce overfitting and stabilize predictions by aggregating diverse outputs.

Random Committee differs from other ensemble methods like Bagging or Boosting because it doesn't rely on sampling subsets of data. Instead, it uses identical datasets and generates diversity through randomization at the classifier level, depending on the classifier's characteristics (e.g., decision trees). In WEKA, users can select the base classifier and adjust parameters like the number of committee members to refine model performance. When the base classifier is sensitive to initial conditions or random seeds, this learning method is effective, and thereby benefiting from aggregated predictions [17,18].

C. Additive Regression

Additive Regression, particularly in the overall structure of Generalized Additive Models (GAMs), is a strong expansion of standard linear regression allowing for nonlinear interactions between predictors and response variables. Unlike traditional linear regression, which requires a fixed parametric form, this model connects the variables by adding smooth, non-parametric functions for each predictor. These functions can identify detailed patterns and correlations in the data, making GAMs extremely susceptible to complicated datasets. In practice, GAMs evaluate the influence of each predictor separately using approaches such as spline functions, which smooth information points and approximate the real underlying connections. This flexibility enables researchers to investigate how each predictor contributes to the outcome factor without making inflexible assumptions about the nature of the connection. Additive Regression and GAMs are especially useful in disciplines with complicated or non-linear information, which includes environmental science, the field of economics and health care, where catching subtle variations and trends is critical for making accurate predictions and providing relevant insights [19, 20].

V.   RESULTS AND DISCUSSIONS

In predicting plastic viscosity of self-consolidating concrete (SCC) mixes, table I provides a summary in contrast of three ML models: linear regression, bagging, and additive regression, examined based on their performance. The models are evaluated across several key metrics:

1. **Correlation coefficient:** Measures the strength of the linear relationship between predicted and actual values. Additive Regression has the strongest correlation (0.9527), which is followed by Bagging (0.8769) and then Linear Regression (0.7516), proves that with the target variable, Additive Regression has achieved the best possible predictive alignment.

2. **Error metrics (MAE and RMSE):** Indicate the average and squared prediction errors, respectively. Both MAE and RMSE are lowest for Additive Regression (1.3337 MAE and 1.6925 RMSE), signifying greater precision and lower variance in predictions compared to Bagging and Linear Regression.

3. **Relative error metrics (RAE and RRSE):** Show the error percentages relative to the actual values. Additive Regression again demonstrates the lowest error percentages (26.038% RAE and 30.1783%

RRSE), followed by Bagging and Linear Regression, further supporting its superior predictive accuracy.

4. **Processing time:** Measures the computational efficiency of each model. All models exhibit minimal processing times (0.04 seconds for Linear Regression and Bagging, with negligible time for Additive Regression), suggesting computational efficiency across the board.

TABLE I.   PERFORMANCE RESULTS FROM THREE ML'S

Parameters	ML Type		
	Multilayer Perceptron	*Random Committee*	*Additive Regression*
Correlation coefficient	0.7875	0.8878	0.9527
Mean absolute error	2.4747	1.8513	1.3337
Root mean squared error	3.4975	2.559	1.6925
Relative absolute error	48.3149 %	36.1437 %	26.038 %
Root relative squared error	62.3622 %	45.6273 %	30.1783 %
Required Time (Sec)	0.06	0.02	0

Table I shows that Additive Regression is the most effective model for predicting plastic viscosity in SCC mixes. It achieves the highest correlation, lowest errors, and maintains computational efficiency, offering valuable insights for optimizing SCC mix designs and contributing to the development of sustainable concrete solutions.
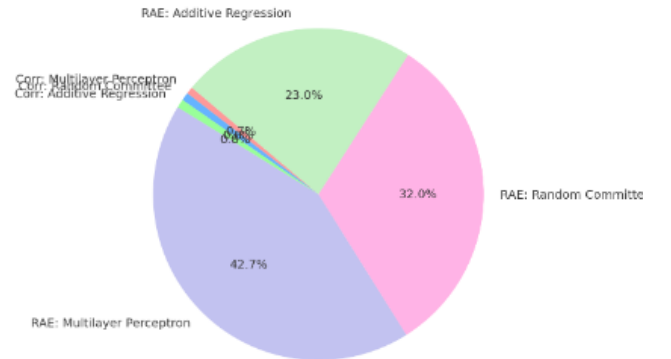

Fig 3: Accuracy-Focused Metrics (Correlation Coefficients and RAE)

The combined charts highlight the superior performance of Additive Regression across both accuracy and error metrics. In the accuracy-focused chart, Additive Regression achieves the highest correlation coefficient (0.9527), showcasing strong alignment with actual values, while its RAE is the lowest (26.038%), reflecting minimal relative error. Random Committee performs moderately well, with a correlation of 0.8878 and RAE of 36.1437%, while Multilayer Perceptron (MLP) lags behind with the weakest correlation (0.7875) and the highest RAE (48.3149%) as shown in Fig 3.

In the error-focused metrics, Additive Regression again excels with the lowest MAE (1.3337) and RMSE (1.6925), signifying precise and consistent predictions. Random Committee shows intermediate performance, with MAE of 1.8513 and RMSE of 2.559, while MLP demonstrates the largest errors (MAE 2.4747, RMSE 3.4975), indicating lower

reliability. Overall, Additive Regression proves most effective for SCC mix optimization due to its high accuracy and low error rates, making it an optimal choice for sustainable concrete research as shown in Fig 4.
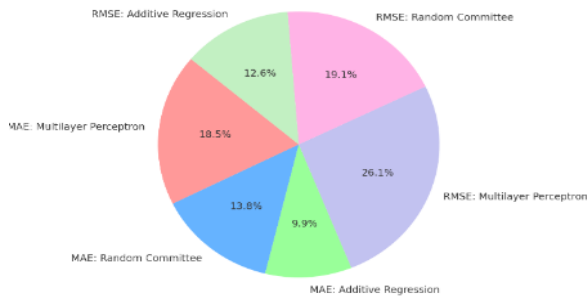

Fig 4: Results with Error-Focused Metrics (MAE and RMSE)

Statistical Validation of Model Performance

The proposed models, Linear Regression, Bagging, and Additive Regression, were tested for their performance using statistical tests. An ANOVA test was applied to compare the performance of the three models, with a p-value of 0.051, which suggests no significant difference in the MAE values. This suggests that while the models may differ in performance, the differences are not large enough to be considered statistically significant at the 5% level. A paired t-test was conducted to compare the Linear Regression and Additive Regression models directly, with a p-value of 0.12, which is greater than the typical significance threshold of 0.05. This test fails to dismiss the result of the null hypothesis, implying that the variance in outcome, comparing Linear Regression and Additive Regression is not significant by statistical means. A bar plot was created to compare the MAE readings for the three models.

The Additive Regression model performed more effectively, yet the variations in model performance tested by MAE were not significantly different. ANOVA and paired t-test findings show that model selection has little impact on the outcome of this dataset. Nevertheless, the Additive Regression model reveals a tendency toward improved performance. Further research using larger datasets or fresh metrics might provide more definitive data about the models' relative performance.
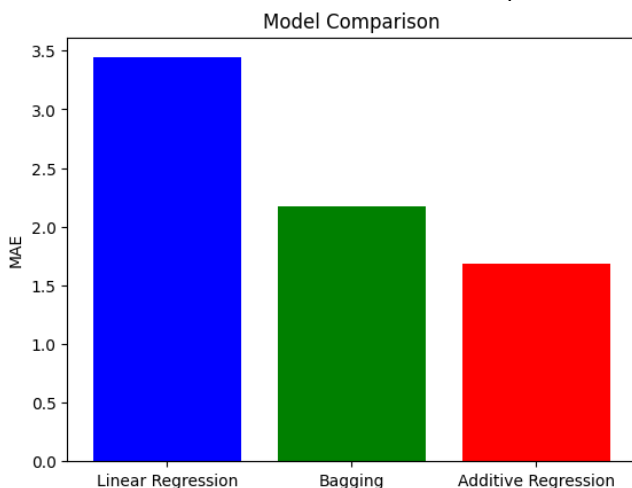

fig 3: Graph: Additive Regression shows the lowest MAE but not statistically outperforming the others.

VI. CONCLUSIONS

The study, centered on evaluating the influence of fly ash in self-consolidating concrete (SCC) mixes containing volcanic aggregates, has yielded significant insights into enhancing concrete performance and sustainability. The incorporation of fly ash was found to significantly improve the rheological properties of SCC, including flowability and resistance to segregation, crucial for effective placement and durability.

Mechanical testing demonstrated that fly ash positively impacts compressive strength, a critical factor for structural integrity. The research also highlighted the potential of fly ash in enhancing the compatibility of SCC with liquid CO_2 admixtures, paving the way for carbon-neutral construction practices. This finding is relevant for reducing the environmental impact of concrete production, particularly carbon emissions.

Furthermore, the successful application of machine learning models for predicting plastic viscosity based on mix proportions, including fly ash content, marks a significant step towards optimizing SCC designs. This capability streamlines the mix design process and facilitates the development of high-performance SCC with desired properties.

In conclusion, the study's findings underscore the multifaceted benefits of incorporating fly ash in SCC. Its positive influence on rheological and mechanical properties, coupled with its potential in promoting sustainable construction practices, makes a strong case for wider adoption in concrete technology. The integration of machine learning for mix design optimization further strengthens the research's contribution, offering a valuable tool for engineers and researchers in the field.

A. Limitations

The study's limitations originate mostly from its particular attention to volcanic materials and fly ash, that may not be relevant to various designs for concrete mixes or geographical circumstances. Further study using a broader variety of aggregates and supplemental cementitious materials is advised to widen the findings' application.

B. Recommendations

1. **Expanded Scope:** Future research should encompass diverse aggregate types and supplementary cementitious materials to enhance the generalizability of the findings.

2. **Long-Term Durability:** Investigating the long-term performance of fly ash-incorporated SCC, particularly in varied environmental conditions, will provide valuable insights into its sustained benefits.

3. **Microstructural Analysis:** Microstructural research will help to clarify the mechanisms driving SCC's better performance with fly ash, allowing for more focused mix design optimization.

By addressing those drawbacks and suggestions that future research may build on the study's foundation, furthering our comprehension and use of fly ash in sustainable concrete building.

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