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Machine Learning-based Prediction of Properties of Geopolymer Concrete with Comparative Cost Analysis

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***Abstract*— GPC is one of the sustainable construction materials. It has a low carbon footprint and good durability. However, predicting mechanical performance and durability related to composition is one of the key challenges compared to Portland cement. This research presents a machine learning–driven predictive framework for evaluating the essential characteristics of geopolymer concrete, including both fresh and hardened properties. In this study, multiple machine learning models are developed, for example, RF, SVG, GB, and ANN. The simulations are assessed using execution metrics, including RMSE, R^2, and MAE. This combined approach provides engineers, researchers, and field practitioners with a robust tool to support decision-making for improving mix design and evaluating the cost-effectiveness of geopolymer concrete. The results determine that the proposed ML models can accurately predict GPC properties with high generalization capability.**

***Keywords*— Geopolymer concrete, Machine learning, Sustainable construction materials.**

I. Introduction

Machine learning, being part of artificial intelligence, has helped to develop concrete with improved strength and cost efficiency [1]. While developing and analysing models side by side, it helps to identify the best-performing model with good accuracy. ML also help to predict the structural properties of concrete. In 1978, the term geopolymer was coined by Davidovits. GPC is produced through the activation of silica-rich materials with an alkaline solution, which comprises sodium or potassium silicate and sodium or potassium hydroxide [2–4]. This research explores new possibilities for developing eco-friendly concrete. Authors seek to predict the mechanical and economic performance of GPC by utilizing advanced machine learning methods combined with an in-depth cost–emission assessment. Authors are developing a computational system that considers factors such as the composition of glass powder and fly ash, the quantities of activators, and curing details, which will lead to predictions of compressive, tensile, and flexural strength [5].

GPC mixtures can be rather intricate, as their properties are affected by numerous chemical and physical factors; thus, an extensive dataset is required to encapsulate all these varying components [6,7]. A GPC is a better alternative material to normal concrete because of its various advantages over normal concrete, as it produces less carbon emission, and therefore most popular material in the construction industry [6–8]. GPCs are classified as alkali-activated cements [9,10].

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In practice the best method that generally followed in construction site is that mixing of alkali activators in dry material, the other method is also available to produce GPC [11,12].

II. Materials and Methodology

The materials used for this research work are waste mix glass powder, fly ash, CDW, and alkali activators [13]. All materials are accumulated from the local area. The research Methodology defines the systematic process adopted to design, develop, train, and validate the ML-Based Prediction Model for GPC integrated with Comparative Cost Analysis.

The project was developed in the context of using a machine learning algorithm to avoid the typical old method. The steps involve data collection and preparation, model development using ML algorithms, evaluation and optimization and deployment and result interpretation.

Data collection is being done by filtering and extracting the detailed data from the existing research paper. The key factors like Fly ash or GGBS content (% by mass), NaOH molarity (M), Na_2SiO_3/NaOH ratio, Activator-to-binder ratio, Binder-to-aggregate ratio, curing temperature (°C) and duration (hours), Water/binder ratio, Type of aggregates and chemical admixture are considered for model design. The process for training the model is data Cleaning, standardisation, feature encoding, dataset splitting (80% and 20%), and outlier detection. This helps to identify that the data is not relatively close to most of the data. Feature importance is analyzed using Correlation Heatmaps, Random Forest Feature Importance Ranking, Variance Inflation Factor (VIF). The next phase involves training multiple supervised ML models to predict concrete properties. The LR, RF, GB, and ANN Hyperparameter tuning is carried out using Grid Search CV and Cross-Validation (k=10) to determine the optimal configuration for each algorithm.

The trained models are evaluated using the performance metrics like Coefficient of Determination (R^2), Mean Absolute Error, Root Mean Square Error, and Mean Percentage Error. A Predicted vs. Actual Strength plot is generated to visualise model accuracy. The model with the best performance (highest R^2 and lowest RMSE) is selected for final deployment.

The model is very efficiently differentiated in terms of costing as per the produced GPC grade. Compared with experimental and existing data, the validation of the current model [12,14].

III. Results and Discussion

A. Cost Analysis

The comparison of hazardous gas emissions between Conventional M40 Concrete and Geopolymer Concrete (GPC) is shown below. Portland cement is dangerous. Emissions are extremely damaging. Recent estimates of cement production emissions show that 377 million metric tonnes of carbon were produced in 2022, indicating that emissions from fossil fuel combustion and cement production have more than doubled since the mid-1970s [15].

Table 1 and Table 2 Shows the cost analysis of traditional and geopolymer concrete.

TABLE I. COST ANALYSIS OF TRADITIONAL CONCRETE

Material	Cost (₹)	Percentage of Total Cost (%)
Cement	2800	53.95%
Sand (Fine Aggregate)	990	19.07%
Coarse Aggregate	1400	26.98%
Water	0	0%
Total	5190	100%

TABLE II: COST ANALYSIS OF GEOPOLYMER CONCRETE

Material	Quantity (kg)	Unit Cost (₹/kg)	Total Cost (₹)
Fly Ash	270	3	810
Waste Mix Glass Powder	115	2 (Grinding Cost)	230
Sodium Hydroxide Pellets	45	60	2700
Sodium Silicate Solution	110	29	3190
Mix CDW (Brick Waste & Concrete Waste) – Fine Aggregate	850	0.5	425
Fly Ash Coarse Aggregate (Material +			
Processing Cost = ₹3/kg)	1100	3	3300
Water (~50 liters)	50	—	0
Total Cost per m³ of GPC	—	—	₹10,655/-

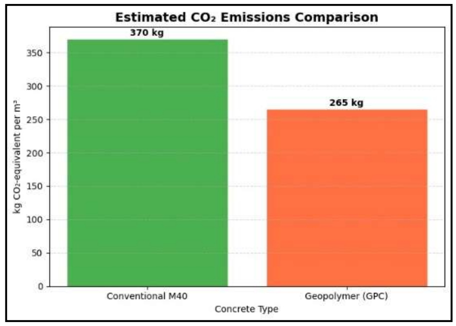


Figure 1 CO2 Emission Comparison

B. Effect of Alkali Activator Reduction on Cost and Emissions

Figure 1 illustrates that the influence of Alkaline activator content, specifically SH and SS, has an impact on the overall cost and CO_2 emissions related to the manufacture of Geopolymer Concrete (GPC), as seen in the graph above. The Y-axis displays two important parameters: the estimated CO_2 emissions (kg CO_2) and the overall production cost (₹). The X-axis shows the various amounts of NaOH used in the mix [16,17]. As can be seen, the cost and emissions gradually increase as the NaOH content rises. This is because the costliest parts of the GPC mix, NaOH and Na_2SiO_3, need energy- intensive production methods, which raises the embodied carbon. The total cost per cubic meter of GPC increases from about ₹7,000 to ₹8,800 when the activator dosage increases from 25 kg to 45 kg. CO_2 emissions also slightly increase during this time. The trade-off is higher material expense and environmental effect, even if larger activator concentrations improve early strength and bonding by increasing the efficiency of the polymerization reaction. The Figure 2 and 3 illustrate the relationship between the quantity of NaOH used as an activator in Geopolymer Concrete (GPC) and the resulting mechanical strength properties, including compressive, tensile, and flexural strength. The X-axis represents the NaOH quantity (in kg), while the Y-axis denotes the corresponding strength values (in MPa).

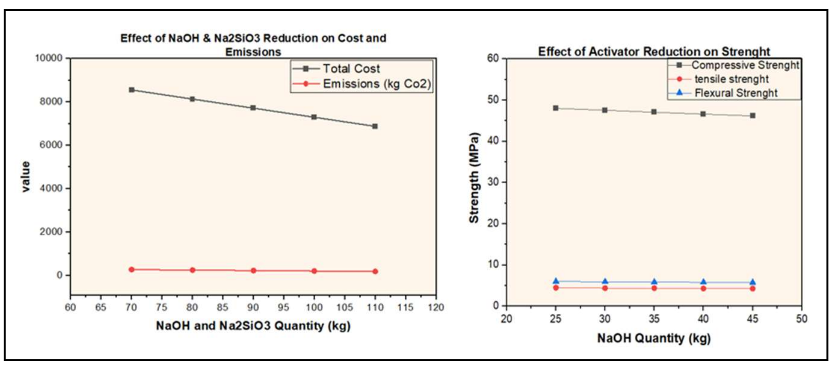


Figure 2: Relation between the alkali activator, cost and strength

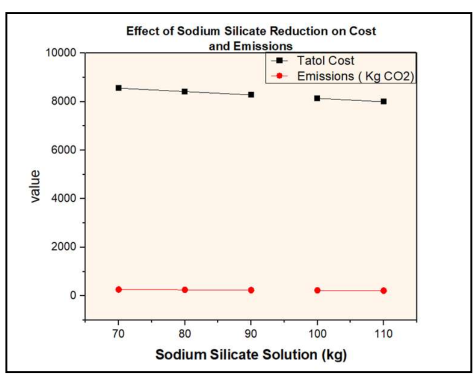


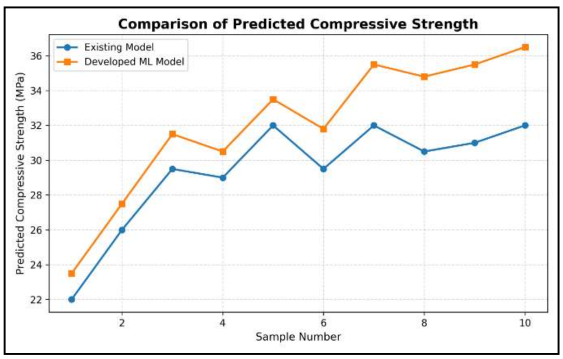
Figure 3: Effect of sodium silicate Reduction on cost and emission.

C. Combined Effect of SH and SS on Cost, Emissions, and Strength

The Figure 4 and 5 present a comparative analysis of predicted compressive strength versus actual compressive strength for Geopolymer Concrete (GPC) using three different predictive models — Linear Regression, Random Forest, and the Developed Machine Learning (ML) Model. The X-axis represents the actual compressive strength values (in MPa), while the Y-axis corresponds to the predicted compressive strength (in MPa) obtained from each model. Table 3 shows the combined effect of the alkali activator on strength properties.

TABLE III: COMBINE EFFECT OF THE ALKALI ACTIVATOR FOR STRENGTH PROPERTIES

Type	NaoH	Na2SiO3 Kg	Total Cost	Emissions Kgco2	Compressive Mpa	Tensile Mpa	Flexural Mpa
NaoH	45	110	8555	263.65	48	4.5	6
NaoH	40	100	8135	241.66	47.54	4.4	5.94
NaoH	35	90	7715	219.66	47.07	4.4	5.88
NaoH	30	80	7295	197.66	46.61	4.3	5.83
NaoH	25	70	6875	175.66	46.14	4.3	5.77
Na2SiO3	45	110	8555	263.65	48	4.5	6
Na2SiO3	45	100	8415	251.66	47.69	4.4	5.95
Na2SiO3	45	90	8275	239.66	47.38	4.4	5.89
Na2SiO3	45	80	8136	227.66	47.07	4.4	5.84
Na2SiO3	45	70	7995	215.66	46.76	4.3	5.78



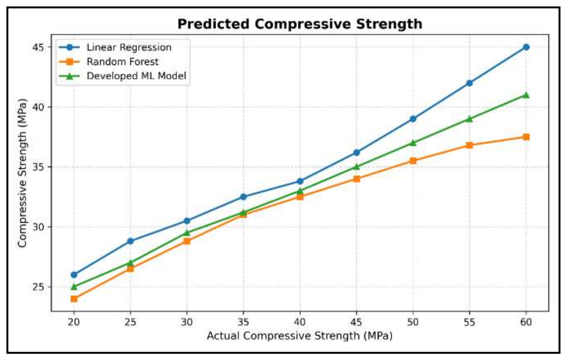


Figure 4: Comparison of strength results for current and existing models   Figure 5: Predicted compressive strength for different models

IV. CONCLUSIONS

This research shows that various parameters, which are related to each other, play a strong role in determining the mechanical performance and cost efficiency of GPC, such as the content of alkaline activators, binder composition, curing conditions, and aggregate characteristics. The findings confirm that an increase in the concentration of SH and SS increases strength development as a result of better geo-polymerisation, although the increase in material cost and embodied CO2 emissions is observed, too. The created machine learning-based predictive model was able to emulate the nonlinear correlations between mix design variables and major performance indices, including compressive, tensile, and flexural strength. The optimized ML model was one of the models that were evaluated and had high prediction accuracy and good generalization capacity, which makes it a good tool in the estimation of the performance of GPC mixtures. The fact that there was a close correlation between the experimental results and the predicted results is a testament to the strength of the proposed approach.

Moreover, the integrated cost and emission analysis indicates that it is possible to find a balance in trade-off between mechanical performance, financial viability, and environmental sustainability by optimizing the alkaline activator dosage. The results show that geopolymer concrete can be made much less carbon-emitting than traditional cement-based concrete and with the same structural performance, using a data-driven optimization technique. On the whole, this study supports the fact that machine learning, together with cost-emission assessment is an efficient decision-supporting instrument in the process of developing sustainable geopolymer concrete. The suggested framework should help the engineers and scientists in creating optimized GPC mixes having better performance, less costly and having less environmental impact, which will lead to the increased usage of geopolymer concrete in sustainable building projects.

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