International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 15 Issue 5, May-2026

Machine Learning-Based Strength Estimation and Structural Behavior of Eco-Friendly Ternary Geopolymer Concrete: A Review

Vijay Verma[1], Dr. Sudesh Kumari[2]

[1]M.Tech. Scholar (Structural Engineering), BMU, Rohtak
[2]H.O.D., Asst. Prof., Civil Engineering Department, BMU, Rohtak

ABSTRACT

The construction industry is one of the major contributors to global carbon dioxide emissions due to extensive utilization of Ordinary Portland Cement (OPC). To minimize environmental impacts and promote sustainable construction materials, geopolymer concrete (GPC) has emerged as an effective alternative. Among various forms of geopolymer concrete, ternary geopolymer concrete prepared using three aluminosilicate source materials such as fly ash, ground granulated blast furnace slag (GGBS), silica fume, rice husk ash, or metakaolin exhibits enhanced mechanical and durability characteristics. Simultaneously, the application of Machine Learning (ML) techniques in civil engineering has gained remarkable attention for predicting strength and structural behavior with high precision and reduced experimental cost. This review paper presents a comprehensive overview of eco-friendly ternary geopolymer concrete and the application of machine learning algorithms for strength estimation and structural performance prediction. The study critically discusses the constituent materials, mix design parameters, fresh and hardened properties, durability characteristics, and structural behavior under various loading conditions. Furthermore, recent advancements in ML models such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Gradient Boosting, and Deep Learning techniques are reviewed for compressive strength prediction and performance assessment. The paper also highlights existing research gaps, challenges, and future opportunities in integrating sustainable geopolymer technology with intelligent computational methods.

Keywords: Ternary geopolymer concrete, Machine learning, Compressive strength prediction, Eco-friendly concrete, Structural behavior, Sustainable construction, Artificial intelligence.

1. INTRODUCTION

Rapid urbanization and infrastructure development have substantially increased the demand for cement-based construction materials worldwide. However, the production of Ordinary Portland Cement contributes approximately 7–8% of global carbon dioxide emissions. The urgent need to reduce greenhouse gas emissions and conserve natural resources has encouraged researchers to explore sustainable alternatives to conventional concrete.

Geopolymer concrete has emerged as a promising eco-friendly material due to its low carbon footprint and superior engineering performance. Unlike OPC-based concrete, geopolymer concrete utilizes industrial by-products rich in aluminosilicate materials activated by alkaline solutions to form polymeric binding gels. Common source materials include fly ash, GGBS, metakaolin, silica fume, and rice husk ash.

Recent developments have focused on ternary geopolymer concrete systems in which three supplementary cementitious materials are combined to optimize strength, durability, workability, and microstructural characteristics. The synergistic interaction among ternary blends significantly improves mechanical and durability properties compared to binary or single-source geopolymer systems.

At the same time, experimental investigation of geopolymer concrete involves considerable cost, labor, and time. Machine learning techniques provide a powerful alternative for predicting concrete properties using historical datasets and intelligent algorithms. ML models can estimate compressive strength, tensile strength, elastic modulus, durability indicators, and structural behavior with high accuracy.
This review paper aims to synthesize current research related to:

- Eco-friendly ternary geopolymer concrete,

- Mechanical and structural behavior,
- Application of machine learning in strength estimation,
- Challenges and future research directions.

2. FUNDAMENTALS OF GEOPOLYMER CONCRETE

2.1 Geopolymerization Mechanism

Geopolymerization is a chemical reaction involving aluminosilicate materials and alkaline activators. The reaction generally consists of:

1. Dissolution of silica and alumina,
2. Transportation and orientation of dissolved particles,
3. Polycondensation into three-dimensional geopolymeric networks.

The generalized geopolymerization reaction can be represented as:

$$M_n\left[-(SiO_2)_z - AlO_2\right]_n \cdot wH_2O$$

where:

- M = alkali metal ion,
- z = degree of polymerization,
- n = polycondensation extent.

3. CONSTITUENT MATERIALS OF TERNARY GEOPOLYMER CONCRETE

3.1 Fly Ash

Fly ash is one of the most commonly used precursor materials due to its high silica and alumina content. Class F fly ash is particularly preferred for geopolymer production.

Advantages

- Improved workability,
- Reduced heat generation,
- Enhanced long-term strength.

3.2 Ground Granulated Blast Furnace Slag (GGBS)

GGBS contributes calcium content that accelerates geopolymerization and improves early strength development.

Benefits

- Faster setting,
- Enhanced durability,
- Better resistance to chloride penetration.

3.3 Silica Fume

Silica fume improves pore refinement and densifies the microstructure.

Effects

- Increased compressive strength,
- Reduced permeability,
- Enhanced interfacial transition zone.

3.4 Metakaolin

Metakaolin contributes reactive alumina and enhances geopolymeric gel formation.

3.5 Alkaline Activators

Common alkaline activators include:

- Sodium hydroxide (NaOH),
- Sodium silicate (Na_2SiO_3),
- Potassium hydroxide (KOH).

4. TERNARY GEOPOLYMER CONCRETE MIX DESIGN

The mix design of ternary geopolymer concrete depends on:

- Source material proportions,
- Alkaline activator concentration,

- Alkali-to-binder ratio,
- Water-to-geopolymer solids ratio,
- Curing temperature and duration.

Important parameters influencing performance include:

- Molarity of NaOH,
- Sodium silicate to sodium hydroxide ratio,
- Aggregate content,
- Superplasticizer dosage.

5. MECHANICAL PROPERTIES OF TERNARY GEOPOLYMER CONCRETE

5.1 Compressive Strength

Compressive strength is the most widely investigated property of geopolymer concrete.
Factors affecting strength include:

- Binder composition,
- Activator concentration,
- Curing conditions,
- Water content,
- Age of concrete.

Typical compressive strength equation:

$$f_c = \frac{P}{A}$$

where:

- f_c = compressive strength,
- P = failure load,
- A = loaded area.

Studies reported compressive strengths exceeding 60 MPa for optimized ternary systems.

5.2 Split Tensile Strength

Ternary geopolymer concrete demonstrates improved tensile strength due to enhanced matrix densification and better particle packing.

5.3 Flexural Strength

Incorporation of silica fume and GGBS significantly improves flexural performance and crack resistance.

5.4 Elastic Modulus

Elastic modulus generally increases with compressive strength and microstructural densification.

6. Durability Characteristics

6.1 Acid Resistance

Geopolymer concrete exhibits superior resistance to acidic environments compared to OPC concrete.

6.2 Sulfate Resistance

Dense geopolymeric matrices reduce sulfate ingress and expansion.

6.3 Chloride Penetration

Low permeability in ternary systems minimizes chloride diffusion.

6.4 Freeze-Thaw Resistance

Well-designed ternary geopolymer mixtures exhibit excellent freeze-thaw durability.

7. Structural Behavior of Ternary Geopolymer Concrete

7.1 Behavior Under Compression

Structural members prepared with ternary geopolymer concrete exhibit enhanced load-carrying capacity due to dense microstructure.

7.2 Flexural Behavior of Beams

- Experimental studies indicate:
- Higher ultimate load capacity,
- Improved ductility,
- Reduced crack width.

7.3 Shear Behavior

Addition of GGBS and silica fume enhances shear resistance and bond performance.

7.4 Seismic Performance

Geopolymer concrete structures show promising energy dissipation capacity and reduced stiffness degradation under cyclic loading.

8. Machine Learning Techniques in Strength Prediction

Machine learning has emerged as a reliable tool for predicting concrete properties using historical experimental datasets.

8.1 Artificial Neural Network (ANN)

ANN models mimic biological neural systems and are highly effective for nonlinear prediction problems.

Advantages

- High prediction accuracy,
- Capability to model complex relationships.

Limitations

- Requires large datasets,
- Prone to overfitting.

8.2 Support Vector Machine (SVM)

SVM is widely used for regression and classification applications.

Benefits

- Effective with small datasets,
- Good generalization capability.

8.3 Random Forest (RF)

Random Forest uses ensemble decision trees for prediction.

Features

- High robustness,
- Reduced overfitting,
- Better handling of nonlinear relationships.

8.4 Decision Tree (DT)

Decision tree algorithms are simple and interpretable.

8.5 Gradient Boosting and XGBoost

Boosting algorithms provide superior prediction performance by sequentially correcting errors.

8.6 Deep Learning Models

Deep neural networks can capture complex interactions among mix design variables.

9. Input Parameters Used in ML Models

Common input variables include:

- Fly ash content,
- GGBS percentage,
- Silica fume dosage,
- Water-to-binder ratio,
- NaOH molarity,
- Sodium silicate ratio,
- Aggregate content,
- Curing temperature,

- Curing duration,
- Superplasticizer dosage.

Output parameters:

- Compressive strength,
- Tensile strength,
- Flexural strength,
- Durability indices.

10. Performance Evaluation Metrics

Machine learning models are evaluated using statistical indicators such as:

10.1 Coefficient of Determination

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

10.2 Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

10.3 Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

11. Research Gaps

Despite extensive studies, several gaps remain:

1. Limited large-scale structural investigations,
2. Lack of standardized mix design procedures,
3. Insufficient long-term durability data,
4. Limited hybrid ML model applications,
5. Scarcity of publicly available datasets,
6. Need for real-time structural health monitoring integration.

12. Future Research Directions

Future studies should focus on:

- Development of hybrid AI models,
- Integration of IoT-based monitoring systems,
- Multi-objective optimization,
- Life cycle assessment,
- Sustainable curing techniques,
- Large-scale field implementation,
- Explainable AI models for civil engineering applications.

CONCLUSION

Eco-friendly ternary geopolymer concrete has emerged as a sustainable and high-performance alternative to conventional concrete. The incorporation of industrial by-products significantly reduces environmental impact while improving mechanical and durability characteristics. Ternary blending systems provide enhanced strength, microstructural densification, and superior long-term performance.

Machine learning techniques have revolutionized the prediction of concrete properties by reducing experimental efforts and enabling rapid performance estimation. Among the reviewed models, Random Forest, ANN, and XGBoost exhibit excellent prediction capability for compressive strength estimation. The integration of sustainable geopolymer technology with advanced computational intelligence presents immense opportunities for next-generation smart construction materials. However, further research is necessary to establish standardization, improve interpretability of ML models, and promote large-scale practical implementation.

REFERENCES

1. Davidovits, J. “Geopolymer Chemistry and Applications.”

2. Hardjito, D., and Rangan, B. V. "Development and Properties of Low-Calcium Fly Ash-Based Geopolymer Concrete."
3. Nath, P., and Sarker, P. "Effect of GGBFS on Setting, Workability and Early Strength Properties of Fly Ash Geopolymer Concrete."
4. Singh, B., et al. "Geopolymer Concrete: A Review of Some Recent Developments."
5. Ahmed, M., et al. "Machine Learning Techniques for Predicting Compressive Strength of Geopolymer Concrete."
6. Chou, J. S., and Pham, A. D. "Enhanced Artificial Intelligence for Concrete Strength Prediction."
7. Behnood, A., and Golafshani, E. M. "Predicting the Compressive Strength of Silica Fume Concrete Using Hybrid Machine Learning Models."
8. Asteris, P. G., et al. "Artificial Neural Network Models for Prediction of Concrete Mechanical Properties."
9. Topçu, İ. B., and Sarıdemir, M. "Prediction of Mechanical Properties of Recycled Aggregate Concretes."
10. Mehta, P. K. "Reducing the Environmental Impact of Concrete."