



Analysis of Strength Prediction Models using Machine Learning for Mongolian Fly Ash Concrete

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Abstract — This paper investigates the application of machine learning (ML) methods for predicting the compressive strength of Mongolian fly ash concrete. Four predictive models—Multiple Linear Regression (MLR), Ridge Regression, Lasso Regression, and Decision Tree Regression—were developed and compared using both experimental data and a benchmark dataset from the UCI repository. The Decision Tree model demonstrated the highest predictive accuracy ($R^2 = 0.95$, RMSE = 3.71 N/mm², MAPE = 8.00%), outperforming all linear regression-based approaches ($R^2 \approx 0.57$). The novelty of this work lies in its focus on Mongolian high-calcium (Class C) fly ash, whose elevated CaO content and distinct hydration kinetics differ from globally studied Class F fly ashes. These variations in chemical composition and mineral structure result in distinct patterns of strength development, highlighting the importance of developing region-specific prediction models to ensure structural safety, cost efficiency, and sustainability in Mongolian construction practices. The study further provides a foundation for integrating ML-based predictive tools into local engineering practice and design standards.

Keywords—Concrete, Fly Ash, Compressive Strength, Machine Learning, Decision Tree

I. INTRODUCTION

Concrete plays a central role in modern civil engineering, providing the backbone for infrastructure such as bridges, highways, buildings, and power facilities. Its compressive strength is the most critical parameter determining safety, durability, and long-term serviceability of structures [1]. With rapid urbanization and industrial development, demand for concrete has surged globally, and especially in emerging economies such as Mongolia. Mongolia is undergoing a construction boom driven by housing projects, infrastructure expansion, and policy reforms. This rapid growth intensifies the need for efficient quality control systems that can reliably

predict the mechanical properties of concrete before structural application [2].

Fly ash, a by-product of coal-fired power plants, has become a widely recognized supplementary cementitious material (SCM). Globally, fly ash is known to enhance workability, durability, and sustainability of concrete by reducing cement consumption and associated CO₂ emissions [3]. In Mongolia, where approximately 93% of electricity is generated from coal, fly ash is produced in large quantities, predominantly of the high-calcium (Class C) type [2]. The chemical composition of Mongolian fly ash, particularly its elevated CaO content, distinguishes it from the low-calcium (Class F) fly ashes commonly reported in international literature [1]. This compositional difference results in distinct hydration kinetics and strength development behaviors, necessitating region-specific research.

Traditional prediction methods for compressive strength—such as empirical equations and regression-based models—have long been employed in construction practice [4]. While these approaches offer interpretability and simplicity, they struggle with non-linear material interactions, multicollinearity, and variability in local raw materials [2]. As a result, inaccurate predictions may occur: overestimating strength in the early stages can lead to premature demolding and structural failures, while underestimation in later stages may cause conservative mix designs, inflating costs and resource consumption [1]. This distinction provides the main novelty of the study, as it applies machine learning methods to a uniquely Mongolian material system that has not been quantitatively analyzed in prior international research.

Recent advancements in Artificial Intelligence (AI) and machine learning (ML) have revolutionized predictive modeling across various engineering domains. In the field of concrete technology, methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and

Decision Trees have demonstrated superior accuracy compared to linear models [3]. These approaches are capable of capturing complex, non-linear interactions among multiple input parameters—including cement content, fly ash replacement ratio, water-to-binder ratio, curing conditions, and testing age—without requiring explicit physical equations. Importantly, ML can adapt to local datasets, making it a promising tool for addressing Mongolia's unique fly ash properties.

Despite these promising advances, challenges remain. The performance of ML models heavily depends on the availability and quality of training data. In Mongolia, datasets are often limited, fragmented, or inconsistent due to a lack of systematic experimental programs [2]. Moreover, while black-box models like ANN can achieve high accuracy, their interpretability is limited, creating difficulties in practical engineering decision-making. This study therefore aims not only to apply machine learning but also to critically compare different models—Multiple Linear Regression (MLR), Ridge Regression, Lasso Regression, and Decision Tree Regression—for their accuracy, robustness, and applicability in predicting the compressive strength of Mongolian fly ash concrete.

In particular, the study introduces machine learning as a novel approach for predicting the strength of Mongolian fly ash concrete, combining experimental data with data-driven modeling for the first time in this regional context. This paper makes three major contributions. First, it presents a comparative analysis of four predictive models applied to both experimental Mongolian data and benchmark international datasets. Second, it evaluates their predictive performance across multiple statistical indicators, highlighting the importance of model selection in engineering practice. Third, it demonstrates that Mongolian fly ash concretes exhibit unique strength development trends, underscoring the necessity of region-specific predictive tools. By addressing these points, the study aims to advance data-driven concrete design methods in Mongolia while contributing to the broader discourse on sustainable and intelligent construction.

II. METHODOLOGY

Five fly ash types were considered: four Mongolian high-calcium fly ashes (MNG1–MNG4) and one low-calcium Japanese reference sample [1]. Portland cements from Mongolia and China were used, with natural sand and crushed gravel as aggregates. Concrete mixes were designed with 10–40% fly ash replacement and water-to-binder ratios of 0.39–0.50. Compressive strength was tested at 3, 7, 28, and 91 days following JIS A 1108 [4].

A. Materials

TABLE 1. CHEMICAL AND PHYSICAL PROPERTIES OF FLY ASH

Type of fly ash	Chemical composition [wt. %]							Specific gravity [-]	Surface area [cm ² /cm ³]	Loss of ignition
	SiO ₂	Al ₂ O ₃	Fe ₂ O ₃	CaO	SO ₃	MgO	Others			
MNG1	43.4	12.4	7.1	23.8	4.2	4.6	4.5	2.46	15,409	0.80
MNG2	47.2	14.2	12.0	18.6	1.2	2.2	4.6	2.49	26,096	1.45

MNG3	47.5	13.0	10.8	17.4	2.3	2.8	6.2	2.38	22,298	0.80
MNG4	49.4	13.0	11.0	16.4	1.6	1.9	6.7	2.36	20,242	0.50
JPN	46.3	29.2	7.1	5.0	0.5	0.8	11.1	2.26	15,158	5.70

Commercially available Portland cement was used in all mix designs. A total of six different cement types were employed—two sourced from Mongolia and four from China. Although all are classified as Portland cement, their mechanical performance may vary due to differences in chemical composition and the nature of binders originally incorporated by the manufacturers.

Fine aggregate was sourced from natural sand that passed through a 5 mm sieve, whereas crushed gravel with a maximum particle size of 20 mm was utilized as the coarse aggregate. To maintain uniform workability across all test cases, a high-performance water-reducing admixture based on polycarboxylate ether was added to the mixtures.

B. Mix proportions

The concrete mixtures were prepared with the primary goal of evaluating both the influence of fly ash chemical composition and the effect of varying replacement rates on compressive strength. The water-binder ratio was controlled within the range of 39 to 50% to assure the flowability as well as avoiding the segregation.

Cement replacement ratios by the fly ash ranged from 10% to a maximum of 40% by mass of total binder. Two water-to-binder (W/B) ratios were employed for each fly ash type, tailored to their specific characteristics. To ensure uniform workability across all mixes, the dosage of the superplasticizer was adjusted accordingly. A target slump of 200 ± 20 mm was achieved for all batches, thereby allowing the preparation of comparably compacted and workable concrete specimens. AI systems in medicine require a higher level of computation within the hospital and therefore higher costs for the stronger computers that are used.

C. Specimen preparation and testing

Concrete mixing was conducted using a horizontal one-axis mixer. Cylindrical specimens with a diameter of 100 mm and a height of 200 mm were cast in steel molds. After casting, the specimens were demolded 48 hours later and then water-cured at a controlled temperature of $20 \pm 2^\circ\text{C}$.

Compressive strength tests were performed at 3, 7, 28, and 91 days following the guidelines of JIS A 1108: Method of Test for Compressive Strength of Concrete [4].

III. STRENGTH PREDICTION BASED ON MACHINE LEARNING TECHNOLOGY

In this study, a variety of machine learning methodologies were explored to predict the compressive strength of concrete, leveraging both experimental data and a publicly available dataset. As a baseline, multiple linear regression (MLR) analysis was first applied due to its interpretability and simplicity. Subsequently, more advanced

models, including decision tree regression, Ridge regression, and Lasso regression, were implemented to evaluate their predictive performance and generalization capabilities.

Along with the experimental findings presented in the previous section, this study also utilizes a benchmark dataset from the University of California, Irvine (UCI) Machine Learning Repository. Originally compiled by Yeh [3], this dataset consists of 1,030 samples and includes the following nine input features relevant to concrete mix design: cement content, blast furnace slag content, fly ash content, water content, superplasticizer content, coarse aggregate content, fine aggregate content, and the age of testing. These features are used to predict the compressive strength of concrete.

The integration of machine learning into concrete strength prediction provides a data-driven alternative to empirical or theoretical approaches, potentially enabling more accurate and scalable predictions across varied mix designs and material properties.

A. Multi Linear Regression Analysis

Multiple linear regression (MLR) serves as the initial and most intuitive technique applied in this study. The model was implemented using the built-in regression tool in Microsoft Excel, which provides an accessible platform for non-specialists and practitioners working in industrial settings. MLR models the relationship between a dependent variable (compressive strength) and multiple independent variables by fitting a linear equation to the data. The regression equation is generally represented as:

$$f(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (1)$$

where $f(x)$ is the predicted compressive strength, $x_1, x_2, \dots, x_n$ are the input variables, and $\beta_0, \beta_1, \dots, \beta_n$ are the regression coefficients.

B. Strength prediction based on decision tree method

Decision tree regression is a non-parametric supervised learning method used for continuous output prediction. It constructs a tree-like model of decisions by recursively partitioning the input space based on feature values that minimize prediction error (typically measured by mean squared error in regression).

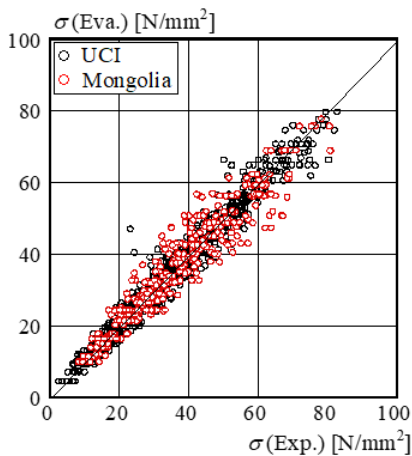


Figure 1: Accuracy of prediction based on decision tree (tree nodes: 198).

C. Strength prediction based on Ridge regression approach

Ridge regression, also known as L2-regularized linear regression, mitigates multicollinearity by adding a penalty term to the loss function, which reduces the magnitude of coefficient values towards zero. The modified loss function is expressed as:

$$\text{Loss} = \sum (y_i - f(x_i))^2 + \lambda \sum \beta_j^2 \quad (2)$$

where λ is a regularization parameter controlling the degree of penalty.

TABLE II. OBTAINED PARAMETERS BY RIDGE REGRESSION METHOD

Variables	Parameters	Symbol	Coefficient
-	Intersect	β_0	36.1
x_1	Cement	β_1	10.7
x_2	Fly Ash	β_2	4.25
x_3	Slag	β_3	7.55
x_4	Water	β_4	-5.68
x_5	Sand	β_5	0.939
x_6	Gravel	β_6	0.163
x_7	Age	β_7	7.71

D. Strength prediction based on Lasso regression method

Lasso regression (Least Absolute Shrinkage and Selection Operator) employs L1 regularization to not only shrink coefficient values but also perform variable selection by driving some coefficients to zero. The loss function includes an L1 penalty term:

$$\text{Loss} = \sum (y_i - f(x_i))^2 + \lambda \sum |\beta_j| \quad (3)$$

TABLE III. OBTAINED PARAMETERS BY LASSO REGRESSION METHOD

Variables	Parameters	Symbol	Coefficient
-	Intersect	β_0	36.1
x_1	Cement	β_1	12.0
x_2	Fly Ash	β_2	5.51
x_3	Slag	β_3	8.95
x_4	Water	β_4	-4.75
x_5	Sand	β_5	2.80
x_6	Gravel	β_6	1.22
x_7	Age	β_7	7.85

IV. RESULTS AND CONCLUSION

This research explored the use of different machine learning methods to predict the compressive strength of concrete, particularly focusing on mixtures containing locally sourced Mongolian materials. By integrating new experimental data with established predictive frameworks, the study addressed both the regional specificity of material properties and the

broader potential of machine learning in practical mix design optimization.

Table IV presents a quantitative evaluation of the predictive performance of multiple regression-based and machine learning models in estimating the compressive strength of concrete, both with and without fly ash incorporation. Among the evaluated approaches, the decision tree model clearly outperforms all others, achieving an R^2 value of 0.950, a root means square error (RMSE) of 3.71 N/mm², and a mean absolute percentage error (MAPE) of 8.00%. This high level of precision underscores the decision tree's capability to effectively accommodate non-linear relationships and capture the underlying variability in concrete strength—especially in datasets characterized by material heterogeneity and multi-source inputs.

In contrast, traditional linear modeling techniques such as multiple linear regression (MLR), ridge regression, and lasso regression yield comparable but significantly less accurate results, with R^2 values around 0.574, RMSE near 10.8 N/mm², and MAPE exceeding 31%. This performance plateau can be attributed to the inherent limitations of linear models, which, while interpretable, struggle to encapsulate the complex interactions between constituent materials—particularly when such interactions deviate from linear behavior.

TABLE IV. PERFORMANCE EVALUATION OF PREDICTION METHODS

Method	R^2	RMSE [N/mm ²]	MAPE [%]	MAE [N/mm ²]
MLR	0.574	10.8	31.5	8.57
Decision tree	0.950	3.71	8.00	2.53
Ridge	0.573	10.8	31.8	8.61
Lasso	0.574	10.8	31.5	8.57

A deeper interpretation of the results, supported by comparative plots in Fig 1 reveals a systematic trend: the group of red markers representing concrete made with Mongolian local materials exhibits a markedly different slope compared to data derived from earlier studies or international sources. This suggests a material-specific divergence in strength development behavior, potentially due to variations in cement fineness, fly ash reactivity, or aggregate mineralogy.

As a consequence, linear models trained predominantly on global or legacy datasets tend to overestimate compressive strength in the low-strength region, while underestimating it for higher-strength concretes. This bi-directional deviation not only threatens structural safety particularly during critical early-age decisions such as demolding, but can also lead to overconservative mix designs, increasing material usage and compromising economic efficiency.

Therefore, to realize the full potential of data-driven mix design, there is a compelling need to expand the regional database of compressive strength tests, especially those using locally sourced Mongolian materials. To strengthen the practical impact, future research should include comparative analyses with other regional fly ashes, validation under different curing conditions, and collaboration with code development bodies to translate these models into engineering practice.

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