Prediction of Compressive Strength of Fly Ash Concrete Using Machine Learning Models

Elahe Moazeni, Yaser Moodi*

Department of Civil Engineering, Sirjan University Of Technology, Sirjan, Iran

ABSTRACT: Fly ash is produced as a byproduct of the coal combustion process in thermal power plants. Fly ash consists of very fine and microscopic particles, typically composed of mineral compounds such as silicon dioxide, aluminum oxide, and iron oxide. These compounds make fly ash suitable for use in various industries, particularly in the construction industry. Applications of fly ash include additives in concrete, fillers in asphalt, production of bricks and concrete blocks, and pollutant absorption. As a pozzolanic material, fly ash helps reduce carbon dioxide emissions in the cement production process. In this study, a comprehensive database of previous studies on fly ash concrete was initially collected. This data included 599 samples from credible laboratory studies. The gathered dataset consisted of various input variables, including the water-to-cement ratio, amount of fly ash, cement content, coarse aggregate amount, fine aggregate amount, superplasticizer content, and curing age of the concrete. To predict the compressive strength of the concrete, various machine learning algorithms were utilized, including Genetic Programming (GP), Adaptive Neuro-Fuzzy Inference System (ANFIS), Multi-Layer Perceptron (MLP), Radial Basis Function Neural Network (RBF), Kriging, and Extreme Learning Machine (ELM). Furthermore, the accuracy of each model was evaluated using statistical indices, and the best model was identified. The results show that different machine learning models exhibit varying performances in predicting compressive strength. In particular, the Kriging method, with a correlation coefficient of 0.96, was selected as the best model.

KEYWORDS

Concrete, Fly Ash, Compressive Strength, Prediction Model, Machine Learning Techniques.

1. INTRODUCTION

Concrete, as the second most widely used material in the world after water, plays a fundamental role in the development of civil infrastructure [1]. However, the cement production process—the primary component of concrete—releases significant amounts of carbon dioxide annually, posing a serious threat to the environment [2, 3]. The use of alternative cementitious materials, such as fly ash as an industrial pozzolan, has been recognized as an effective solution for mitigating adverse environmental impacts while improving the mechanical properties and durability of concrete [4]. Fly ash is produced from the combustion of coal and serves as a partial cement substitute in concrete ,resulting in reduced cement consumption and waste disposal costs while yielding a denser paste [5, 6]. In civil engineering, numerous uncertainties exist that cannot be resolved solely through calculations and experience; therefore, the application of artificial intelligence and machine learning methods has become essential [7, 8]. In recent years, these technologies have been widely employed to predict the properties of concrete. Machine learning algorithms are capable of deriving more accurate relationships for estimating concrete behavior by analyzing input variables compared to traditional methods [9, 10]. In the present study, to address this gap, a comprehensive database comprising 599 valid laboratory mix designs was compiled. Furthermore, the performance of five advanced machine learning algorithms—namely, ELM, ANFIS, MLP, RBF and Kriging—was evaluated within a comparative framework for estimating compressive strength. Additionally, a sensitivity analysis was conducted to determine the precise impact of input variables such as cement ,water, superplasticizer, and aggregates. The key innovation of this research, beyond the development of black-box models, is the provision of an explicit and practical mathematical relationship derived from Genetic Programming (GP). This formulation enables civil engineers to estimate the compressive strength of fly ash-containing concrete with acceptable accuracy without the need for complex computational tools.

* y.moodi.civil@sirjantech.ac.ir

2. METHODOLOGY

In this research, aiming to predict the compressive strength of fly ash concrete, a comprehensive database comprising 599 samples extracted from reputable international articles has been used. This dataset includes 7 input parameters, and compressive strength (fc) is considered as the target variable. After examining the descriptive statistics and data distribution using histograms, the data were randomly divided into two parts: 70% for training and 30% for testing. To enhance the efficiency of the models ,all data were normalized within the range of 0.1 to 0.9. For modeling and prediction, six different methods based on machine learning were employed: Genetic Programming, which evolves function trees to extract an explicit equation and eliminates irrelevant variables [11, 12]; Adaptive Neuro-Fuzzy Inference System, a hybrid of fuzzy logic and neural networks that calculates the output as a weighted sum of Sugeno rules [13]; Multi-Layer Perceptron with one hidden layer and a hyperbolic tangent activation function, which iteratively adjusts weights to reduce error [14, 15]; Radial Basis Function Neural Network, characterized by a simple architecture, high learning speed, and global pproximation capability suitable for continuous functions [16, 17]; Kriging, a statistical interpolation method based on least squares with a Gaussian correlation function, providing variance and reliability assessment [18]; and Extreme Learning Machine, which uses random weights in the hidden layer and directly computes output weights, offering high speed along with good generalization ability [19]. Finally ,the performance of the models was evaluated using statistical indices :Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Standard Deviation (SD). The criterion for selecting the optimal model was the maximum R^2 value close to 1 and the minimum values of the other error indices.

3. RESULTS AND DISCUSSIONS

In this study, the compressive strength of fly ash concrete was predicted using six machine learning models (GP, ANFIS, MLP, RBF ,Kriging, ELM). The GP model provides an explicit relationship (Equation 1) in terms of the variables cement, fly ash, water, superplasticizer ,coarse aggregate, fine aggregate, and curing age. The statistical indicators of the used methods are presented separately for training and testing samples in Table 1. As shown that in this table, the Kriging model achieved the best performance with a coefficient of determination of 0.999 for training data and 0.96 for testing data, along with the lowest error values. Diagram of predicted results versus experimental results using the Kriging model is shown in Figure 1. Following that, the RBF model and the ELM model ranked next in terms of accuracy, respectively. Although the GP model has lower accuracy, it provides an explicit and practical relationship that can be used without the need for specialized software. Sensitivity analysis showed that cement has the greatest positive effect, while coarse aggregate and water have a negative effect; fly ash as a replacement up to about 36% increases strength, after which a gradual decrease occurs .Curing age has a positive effect (with a higher growth rate in the early days), while superplasticizer has a negligible effect.

$$
\begin{aligned}
f_c = {} & \frac{(0.153d)}{\log Ca} - 0.0767C - 2.74\times10^{-4}(C - W)(Si - Fa) \\
& -2.74\times10^{-4}(Fa + Si)(C - FA) + 17.5\log(\log d)^2 + 0.0767\sqrt{FA} \\
& + \frac{\left(4.44\times10^{-16}\left(4.68\times10^{15}C - 4.68\times10^{15}Ca\right)\right)}{\sqrt{W}\,(FA - 2Si)} - \frac{\left(1.88\times10^{15}W \times Ca\left(\sqrt{Fa\times d}\right)\right)}{1.84\times10^{19}C + 1.84\times10^{19}Si} + 28.9
\end{aligned}
\tag{1}
$$

Table 1. Comparison of the investigated models

	Training samples				**Test samples**			
models	**R^2**	**RMSE**	**MAE**	**SD**	**R^2**	**RMSE**	**MAE**	**SD**
GP	0.765	7.354	5.677	0.313	0.751	7.596	6.034	0.325
ANFIS	0.788	6.83	5.36	0.301	0.765	7.166	5.951	0.344
MLP	0.898	4.841	3.777	0.177	0.84	5.99	4.465	0.214
RBF	0.971	2.576	1.871	0.099	**0.868**	**5.434**	**3.791**	0.189
Kriging	**0.999**	**0.456**	**0.116**	**0.017**	**0.96**	**2.999**	**2.85**	**0.113**
ELM	**0.99**	**0.87**	**1.49**	**0.048**	0.853	6.283	4.38	**0.187**

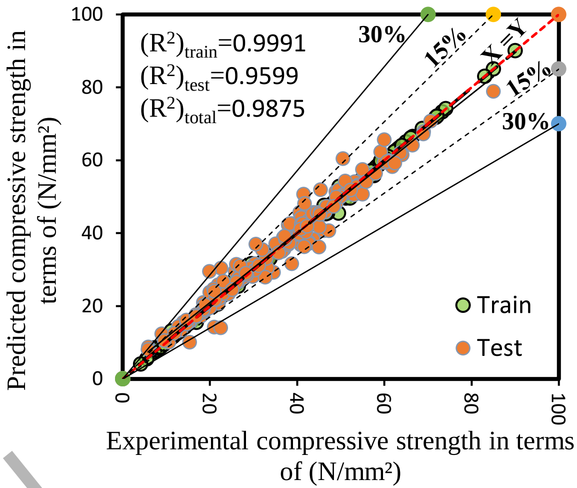

Figure 1. Diagram of predicted results versus experimental results using the Kriging model

4. CONCLUSIONS

This study used 599 samples and six intelligent models to predict the compressive strength of fly ash concrete. The Kriging model achieved the best performance with a correlation coefficient of 0.96. Despite its lower accuracy ($R^2 = 0.751$), the GP model provides a simple and practical relationship. Sensitivity analysis showed that cement, fine aggregate, and curing age have the greatest positive effect, while water has a negative effect. Fly ash as a replacement up to 36% increases strength, after which a decrease occurs. It is suggested that other artificial intelligence methods be used in future studies.

REFERENCES

[1] E. Possan, W.A. Thomaz, G.A. Aleandri, E.F. Felix, A.C.P. dos Santos, CO2 uptake potential due to concrete carbonation: A case study, Case Stud. Constr. Mater. 6 (2017) 147–161. https://doi.org/10.1016/j.cscm.2017.01.007

[2] X. Qian, J. Wang, Y. Fang, L. Wang, Carbon dioxide as an admixture for better performance of OPC-based concrete, J. CO2 Util. 25 (2018) 31–38. https://doi.org/10.1016/j.jcou.2018.03.007

[3] H. Yan, Q. Shen, L.C.H. Fan, Y. Wang, L. Zhang, Greenhouse gas emissions in building construction: A case study of One Peking in Hong Kong, Build. Environ. 45 (4) (2010) 949–955. https://doi.org/10.1016/j.buildenv.2009.09.014

[4] A.A. Shubbar, H. Jafer, A. Dulaimi, K. Hashim, W. Atherton, M. Sadique, The development of a low carbon binder produced from the ternary blending of cement, ground granulated blast furnace slag and high calcium fly ash: An experimental and statistical approach, Constr. Build. Mater. 187 (2018) 1051–1060. https://doi.org/10.1016/j.conbuildmat.2018.08.021

[5] M. Ahmaruzzaman, A review on the utilization of fly ash, Prog. Energy Combust. Sci. 36 (3) (2010) 327–363. https://doi.org/10.1016/j.pecs.2009.11.003

[6] ACI Committee 211, Guide for selecting proportions for high-strength concrete with Portland cement and fly ash, ACI Mater. J. 90 (3) (1993) 272–283.

[7] A.H. Gandomi, X.S. Yang, S. Talatahari, A.H. Alavi (Eds.), Metaheuristic Applications in Structures and Infrastructures, Elsevier, 2013. https://doi.org/10.1016/C2011-0-08778-1

[8] I.S. Alkroosh, P.K. Sarker, Prediction of the compressive strength of fly ash geopolymer concrete using gene expression programming, Comput. Concrete 24 (4) (2019) 295–302. https://doi.org/10.12989/cac.2019.24.4.295

[9] L. Mahajan, S. Bhagat, An artificial neural network for the prediction of the strength of supplementary cementitious concrete, Res. Eng. Struct. Mater. 8 (2) (2022) 421–430. https://doi.org/10.17515/resm2022.341st0918tn

[10] D.C. Feng, Z.T. Liu, X.D. Wang, Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach, Constr. Build. Mater. 230 (2020) 117000. https://doi.org/10.1016/j.conbuildmat.2019.117000

[11] M.N. Al-Hashem, M.N. Amin, M. Raheel, K. Khan, H.A. Alkadhim, M. Imran, Sh. Ullah, M. Iqbal, Predicting the Compressive Strength of Concrete Containing Fly Ash and Rice Husk Ash Using ANN and GEP Models, Mater. 15 (21) (2022) 7713. https://doi.org/10.3390/ma15217713

[12] S. Silva, GPLAB: A Genetic Programming Toolbox for MATLAB, (2007).

[13] H. Citakoglu, M. Cobaner, T. Haktanir, O. Kisi, Estimation of monthly mean reference evapotranspiration in Turkey, Water Resour. Manag. 28 (1) (2014) 99–113. https://doi.org/10.1007/s11269-013-0474-1

[14] N. Safaeian Hamzehkolaei, N. Kadkhoda, An efficient ranked Voronoi diagram-based hybrid method for reliability-based structural analysis and design optimization, Soft Comput. 27 (19) (2023) 13889–13910. https://doi.org/10.1007/s00500-023-08450-z

[15] J.J. Moré, The Levenberg–Marquardt algorithm: Implementation and theory, Lect. Notes Math. 630 (1978) 105–116. https://doi.org/10.1007/BFb0067700

[16] F. Girosi, T. Poggio, Networks and the Best Approximation Property, Biol. Cybern. 63 (3) (1990) 169–176. https://doi.org/10.1007/BF00195855

[17] E.J. Hartman, J.D. Keeler, J.M. Kowalski, Layered Neural Networks with Gaussian Hidden Units as Universal Approximations, Neural Comput. 2 (2) (1990) 210–215. https://doi.org/10.1162/neco.1990.2.2.210

[18] A.Gh. Dehvari, M. Miri, M.R. Sohrabi, Determining Optimum Percent of Recycled Coarse Aggregates used in Corrosive Environment Based on Kriging Model, Amirkabir J. Civ. Eng. 53 (3) (2021) 197–200. https://doi.org/10.22060/ceej.2019.16560.6299

[19] A.K. Al-Shamiri, J.H. Kim, T.F. Yuan, Y.S. Yoon, Modeling the compressive strength of high-strength concrete: An extreme learning approach, Constr. Build. Mater. 208 (2019) 204–219. https://doi.org/10.1016/j.conbuildmat.2019.02.165