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A Comprehensive Review of Machine Learning and Traditional Models for Predicting the Physical and Mechanical Properties of Cement and Cement Mortar

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Abstract

Traditional methods of testing the physical and mechanical properties of cement and cement mortar are reliable, but they are time-consuming and labor-intensive. Therefore, it is necessary to develop robust and consistent models that can reduce dependency on prolonged experimental testing. In this review, different types of models are critically examined, including both machine learning and traditional approaches. The complexity of cement hydration, chemical properties, and microstructural development presents challenges for predictive modeling, but several models have yielded satisfactory results. This review includes various Machine Learning (ML) models such as Back-Propagation Neural Network (BPNN), Support Vector Machine (SVM), Decision Tree, Random Forest (RF), AdaBoost, k-Nearest Neighbors (k-NN), a hydration reaction analysis model, hybrid SVM-Genetic Algorithm (GA), Deep Convolutional Neural Network (DCNN) with Particle Swarm Optimization (PSO), contact mechanics approach, Extreme Gradient Boosting (XGBoost), Gradient Boosting Regression, fuzzy logic-based model, Physics-Informed Neural Network (PINN-CHK), Deep Neural Network (DNN) with Generative Adversarial Networks (GANs), and Group Method of Data Handling (GMDH). In addition, mathematical and numerical models have been studied to predict cement hydration kinetics, compressive strength, microstructure evolution, slurry behavior, and hydration heat. These include MATHCAD7, Scheffe's simplex technique, continuum-based hydration models, constitutive equations, integrated numerical models, and thermodynamic and finite element models. Such predictive models can significantly accelerate decision-making in cement technology. The insights presented in this review will serve as a valuable reference for researchers and engineers.

Major Findings: *This study highlights that traditional testing methods used for cement and mortar are reliable, but they are time-consuming. Several ML and mathematical models have demonstrated strong forecasting capabilities. A few models, such as SVM-GA, DNN-GANs, and PINN-CHK, have shown excellent accuracy. These models can save significant time and enable faster decision-making in the construction sector.*

Keywords: *Cement Strength Prediction, Data-Driven Approaches, Machine Learning Models, Numerical Modeling*

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1.0 Introduction

Due to the growing population demand in the construction industry is also increasing day by day. To cater this increased demand construction industry seeks innovative techniques methods which will save the time and efforts. As per records in current the world after water concrete is a second highest material consumed by today's generation. Cement is one of the most important ingredients of concrete and mortar. So, the manufacturing demand of cement is huge but after manufacturing it has to go some mandatory physical and mechanical testing. Initial and final setting time of cement is very important properties of cement some time they play crucial role. Selection of particular type cement for specific purpose depends on time required to hard or set and compressive strength of cement. In other words, we may say the speed of construction depends on hardening time and compressive strength. So, manufacturing company as well as RMC plants has to be test before its usage. But the testing of cement is very much time consuming and labour intensive. So, in the today's fast world everyone wants quick and reliable techniques for testing which will serve their purpose. Conventionally we test the setting time by Vicat apparatus and compressive testing by casting cubes for different periods which will decide the specific purpose of cement. So to overcome this problem many researchers, engineers tried different methods to predict these results of testing. They developed mathematical models and Artificial Intelligence (AI)- based models for more efficient and reliable predictions. A mathematical model includes hydration kinetics, empirical correlations, and regression-based equations gives valuable information's but they struggle with complex nonlinear relations between cement component, additives and environmental factors. Figure 1 shows network diagram of authors and model used for their research.

AI-based models, like Artificial Neural Networks (ANN), fuzzy logic, Support Vector Machines (SVM), and deep learning techniques, have shown superior performance of prediction. Models are trained from experimental dataset. These models have proved high accuracy in estimating cement setting time and compressive strength.

2.0 Machine Learning (ML) Models Used

In the current review paper machine learning models are evaluated separately and in Table 1 summarizes key machine learning models, including the author names,

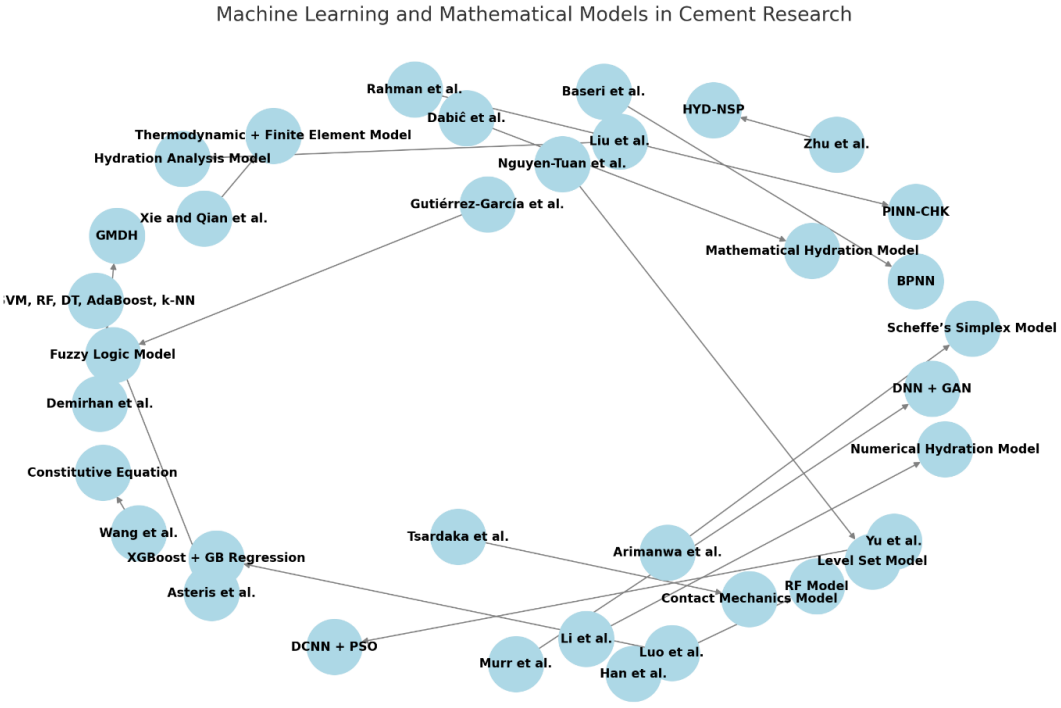


Figure 1. Network diagram.

Tabel 1. Machine learning model

Author(s)	Model Used	Key Findings
Baseri *et al.*[1]	Back-Propagation Neural Network (BPNN)	Accurate prediction of physical and mechanical properties for HA bone cement. $NaH_2PO_4{\cdot}2H_2O$ accelerates setting.
Asteris *et al.*[2]	SVM, Random Forest (RF), Decision Tree, AdaBoost, k-NN	RF and AdaBoost provided precise predictions. Advanced ML techniques improved mix design optimization.
Yu *et al.*[3]	Deep Convolutional Neural Network (DCNN) with Particle Swarm Optimization (PSO)	Achieved $R^2 = 0.999$. Predicts compressive strength under sulfate attack. Useful for predictive maintenance.
Tsardaka *et al.*[4]	Contact mechanics approach	Setting time increases with higher w/c ratio; compressive strength decreases. Model linked setting time with modulus values.
Luo *et al.*[5]	Extreme and boosting gradient, regression	High accuracy in predicting compressive strength of MSHC. Curing age was the most critical factor.
Gutiérrez-García *et al.*[6]	Fuzzy logic model	Electrical resistivity correlates with compressive strength. Higher resistivity indicates lower strength.
Han et al.[7]	Random Forest (RF)	Age and OPC content are the most significant predictors. ML models should be customized for cement chemistry.
Rahman *et al.*[8]	Physics-Informed Neural Network (PINN-CHK)	Relative L^2 error of 0.00341. Outperforms deep learning and FEM in predicting early-age cement hydration.
Murr *et al.*[9]	Deep Neural Network (DNN), TGAN, CTGAN	Predicts tensile behavior of cement pastes. C-S-H, ettringite, and portlandite influence strength.
Demirhan *et al.*[10]	Group Method of Data Handling (GMDH)	High GGBFS replacement (81%) reduces carbon emissions in cement production.
Armaghani Jahed, Sergio Lai, Hamid *al*[18,28,29]	ANN, ANFIS	ANFIS outperformed ANN in predicting compressive strength of cement-based materials.
Gokman, Fa-Liang *et al.*[24,30]	Fuzzy logic model, ANN	Satisfactory prediction of 28-day compressive strength using cement plant data. Compared with ANN for error levels.
Sedat Akkurt *et al.*[26]	ANN with genetic algorithm	Accurate predictions due to limited data range from a 6-month plant dataset.
Marta *et al.*[27]	Neural Network Analysis (NNA) using Trajan neural network simulator	Predicted Unconfined Compressive Strength (UCS) of cement with coal fly ash.
Adil Baykasoglu *et al.*[31,32]	Gene Expression Programming (GEP), Neural Networks (NNs)	GEP is a promising technique for predicting 28-day strength of Portland composite cement.
Yassine El *et al*[33].	7 ML Models (XGBoost was the best)	Alumina-to-silica ratio significantly impacts cement strength development.

models used, their key findings, evaluation metrics (*e.g.*, R^2, relative error), and application contexts, where available. The different studies shows that the models are proved to be quick and with reliable accuracy. Research shows authors used various types of machine learning models for forecast of cement hardening time and compressive strength. Some of them predicted only setting time and few of them predicted both. We will study one by one.

Baseri *et al.*[1] carried out the experimental work on Hydroxyapatite (HA) bone cement and in order to save the time of testing like compressive strength, physical properties of HA cement they also made a ML model of Back-Propagation Neural Network (BPNN). This is one of the types of ANN model. Generally, it is used in prediction, classification, regression, and pattern recognition problems. In the current study input parameters were

liquid concentration and water / powder ratio. The model trained by experimental data. Their model demonstrated high prediction accuracy in estimating the setting time and compressive strength of HA cement, although exact performance metrics were not specified in the study. They also found that $NaH_2PO_4 \cdot 2H_2O$ accelerates the setting reaction of the cement. However, the study was only limited to Hydroxyapatite (HA) bone cement not any other type of cement like Portland cement which is used in construction. These kind prediction models very much useful in construction industry for guess of mechanical and physical properties of cement. Because, cement is the most important ingredient in the concrete.

Asteris *et al.*[2] explored the new machine learning models namely Support Vector Machine (SVM), Random Forest (RF), Decision Tree, AdaBoost, and k-Nearest Neighbors (k-NN). To predict the compressive strength of mortar (1:3). Their main objective was to overcome the drawbacks of artificial neural network like lack of interpretability and over fitting. The input parameters were used such as grade of cement, mortar age, and particle size distribution of sand, plasticizer and water binder ratio. Based on these parameters predictive model is developed. The output of Random Forest and AdaBoost was precise and correct. Outstanding mapping relation between compressive strength and mix proportions. The dataset used for this study was large and taken from previously experimented research. The evaluation of dataset done by models using multiple error metrics. Still, the study did not include microstructural analysis. The findings suggest that advanced ML techniques can improve mix design optimization.

The study by Yu *et al.*[3] developed the deep convolutional neural network model for forecasting the compressive strength of cement-based material under sulphate attack. The model uses Particle Swarm Optimization for more prediction accuracy. The DCNN model proves better than traditional machine learning approaches by achieving R^2 is equal to 0.999. The research highlights that the effect of sulphate exposure leads to progressive deterioration in cement-based materials. The study suggests that PSO-optimized DCNN models can be used for predictive maintenance.

The study by Tsardaka *et al.*[4] developed a predictive model by using a contact mechanics method. Vicat apparatus setting time results were used. The model linked setting time data with modulus values at 28, 90, and 180 days. Two binder types with different w/c ratios were analysed. The model was checked using 28-day strength and modulus values. For higher water binder ratios setting time increases but compressive strength decreases.

The study by Luo *et al.*[5] introduced a predictive model by using extreme gradient boosting and gradient boosting regression. The model estimates compressive strength of Magnesium Silicate Hydrate cement (MSHC). Key factors included like MgO and SiO_2 content. A nonlinear link was observed between strength, S-Mg, and the Mg/Si ratio. The Sensitivity analysis showed curing age was the most critical factor. The current model showed high accuracy.

Fuzzy logic-based model developed by Gutierrez-Garcia *et al.*[6] for forecasting the compressive strength of cement mortars. Electrical resistivity data is used to make the mortar of Pozzolani cement and volcanic sand. The model establishes a correlation between early-age resistivity measurements (within the first 7 days) and 28-day compressive strength. The study demonstrates that higher resistivity values shows to lower strength, and longer curing durations boost strength development. Through experimental validation model accuracy is checked. This research provides efficient mortar evaluation on traditional destructive testing methods.

Han *et al.*[7] identified age and Ordinary Portland Cement (OPC) content is the important parameters for prediction of strength. They explored the application of a Random Forest (RF) model to guess the compressive strength of Limestone Calcined clay cement (LC3). The RF model effectively refined input variables. It minimizes computational complexity and also improves prediction accuracy. The study highlights that calcination temperature, limestone content, and CaO in clay have minimal impact on compressive strength. The findings emphasize the importance of customizing machine learning models from cement chemistry instead of using generic ML approaches.

The model developed by Rahman *et al.*[8] PINN-CHK, a Physics-Informed Neural Network (PINN) demonstrates exceptional accuracy. Shows a relative L2 error as small as 0.00341. They used Partial Differential Equations (PDEs) with data-driven learning. The model is designed for high-fidelity forecast of early-age cement hydration kinetics. Outperforms over conventional deep learning approaches. It achieves reliable predictions with only 5% of training data. As compared to Finite

Element Models (FEM) PINN-CHK offers a mesh-free simulation. For bridging the gap between theory and practical applications. The study highlights its potential for monitoring cement hydration and optimizing curing conditions.

The hybrid approach is developed by Murr *et al.*[9] for predicting the tensile behavior of hydrated cement pastes from its microstructure. A Deep Neural Network (DNN) model was developed. Dataset includes chemical composition, phase volume fractions, and tensile strength of various cement pastes. The results indicate that C-S-H, Ettringite, and Portlandite plays important roll and filled micro porosity, significantly influences tensile strength. The DNN model, supported by synthetic datasets generated via TGAN and CTGAN, was able to accurately estimate tensile strength patterns, though specific accuracy metrics were not reported. To improve dataset diversity, Tabular Generative Adversarial Networks (TGAN) and Conditional GAN (CTGAN) were used. The research provides insights into damage propagation in solid phases and porous networks.

Demirhan *et al.*[10] employs the Group Method of Data Handling (GMDH) machine learning model. They discovered the environmental benefits of nano-modified cement integrating high amounts of Ground Granulated Blast Furnace Slag (GGBFS), replacing cement up to 81%, can reduce carbon emission significantly.

Armaghani Jahed, Sergio Lai, Hamid, Baykasoglu *and* Gullu H *et al.*[18,28,29,31,32] predicted the compressive strength of mortar composed of cementitious materials with or without cementitious material like metakaolin by models such as artificial neural network, ANN and adaptive neuro-fuzzy inference system, ANFIS. Through experimental findings ANFIS is proved better over ANN.

Gokman and Fa-Liang *et al.*[24,30] developed a fuzzy logic prediction model for the 28-day compressive strength of mortar composed with cement. The data used from cement plant, input variables of alkali, Blaine, SO_3, and C_3S were used. The forecast of 50 sets for 28-day cement strength was quite satisfactory. The model was compared with the ANN model for its error levels.

Sedat Akkurt *et al.*[26] used 6 month plant data to make prediction model by ANN. Training and testing data were separated by the use of genetic algorithm. The prediction results were good due to limited data range.

Marta *et al.*[27] predicted Unconfined Compressive Strength (UCS) by adding coal fly ash in the cement using Neural Network Analysis (NNA) based on the Trajan neural network simulator. Adil Baykasoglu *et al*[31,32] used software based computing techniques such as Gene Expression Programming (GEP) and Neural Networks (NNs) to guess 28 days compressive strength Portland Composite Cement (PCC). They concluded GEP is a promising technique for the prediction of cement strength. Yassine El *et al*[33] employed 7 ML models out of that XGboost algorithm appears as the most accurate predictor. Their findings prove that the alumina-to-silica ratio of clay significantly impacts the development of cement strength. In addition to machine learning models, traditional approaches- comprising mathematical, numerical, and analytical models- have also been extensively studied for predicting cement and mortar properties.

3.0 Study of Traditional Models

In the study of traditional models includes mathematical, numerical and analytical models. Table 2 shows models used by the authors and their key findings during research.

Dabic *et al.*[11] made a new mathematical model for predicting cement hydration kinetics. The model mixes multiple hydration processes occurring simultaneously and sequentially. They validated their model using DSC data by quantifying $Ca(OH)_2$ content in cement pastes. Their findings highlight that hydration follows complex kinetics. For accurate prediction requires advanced modeling. They made use of mathematical software MATHCAD.

Arimanwa *et al.*[12] developed a mathematical model of predicting compressive strength by using Scheffe's simplex technique. They studied the effect of OPC'C chemical Composition on 5 different cement brands of South Eastern Nigeria. They concluded from their findings that higher with higher $CaO + SiO_2$ content produced stronger concrete. The model is developed on the basis of results obtained from testing of 300 concrete cubes. Their study also proves that same chemical composition lead to comparable strength properties. Predictive models can help engineers choose optimal cement types can avoid time consuming extensive trial-and-error methods.

Zhu *et al.*[13] established continuum-based Hydration model (HYD-NSP), they replicated the microstructure evolution from the fresh state to the hardened state. The study found that relative diffusivity increases

Tabel 2. Traditional model table

Model Type	Model Name or Approach	Author(s)	Key Features
Mathematical models	Cement hydration kinetics model	Dabic *et al.*[11] (MATHCAD7)	Uses multiple hydration processes and DSC data validation.
	Strength prediction model (Scheffe's simplex)	Arimanwa *et al.*[12]	Predicts compressive strength based on OPC chemical composition.
	Regression models (Full quadratic, non-linear, multi-linear)	Ahmed *et al.*[19]	Uses large datasets for cement paste strength prediction.
	Vipulanandan correlation model	Kawan Ghafor *et al.*[20]	Compares mechanical properties of silica-fume-modified mortar.
	Chemical-mineralogical strength model	S. Tsivilis *et al.*[25]	Examines fineness, chemical composition, and strength at 7 and 28 days.
Numerical models	Continuum-based hydration model (HYD-NSP)	Zhu *et al.*[13]	Simulates microstructure evolution of cement hydration.
	High-temperature slurry rheology model	Wang *et al.*[14]	Predicts yield stress and viscosity under different W/C ratios.
	Hydration, viscosity and ultrasonic prediction model	Li *et al.*[15]	Predicts strength development of class G cement under high pressure.
	Hydration heat prediction (Thermodynamic and FEA)	Xie and Qian *et al.*[16]	Integrates Fourier's law, hydration kinetics, Arrhenius equation.
	Microstructural evolution model (Level set method)	Nguyen-Tuan *et al.*[17]	Captures phase transformations, C-S-H formation, and dissolution.
Analytical Models	Elastic properties prediction model	Baoyu Ma *et al.*[21]	Focuses on hydration, percolation, and homogenization of cement paste.
	Hybrid analytical-numerical elastic modulus model	Y. Gao *et al.*[22]	Uses X-ray CT imaging and ultrasonic wave tests.
	Aging elasticity micromechanics model	O. Bernard *et al.*[23]	Studies elasticity of cement-based materials using 11 mix parameters.

with increasing particle sphericity. This indicates that non-spherical cement grains contribute to a denser microstructure. As higher sphericity leads to fewer hydration products and increased porosity. From their findings suggest that cement particle shape plays a crucial role.

Wang et al.[14] investigated how high temperatures (30° C-80° C) and hydration time influence the rheological behavior of Portland cement slurry. They focused on yield stress and viscosity under different water-cement ratios (W/C: 0.5 to 2.0). Their study shows that higher temperatures significantly increase yield stress and viscosity with reducing the flowability of the slurry. The researchers developed a constitutive equation to predict slurry behavior under extreme conditions, which is useful for grouting applications in deep rock masses.

The study by Li *et al.*[15] explores the hydration, viscosity evolution, and ultrasonic properties of Class G cement under high-temperature and high-pressure conditions. Numerical model is developed by integrating hydration kinetics, rheological behavior and porosity to predict the setting time and strength development of Class G cement. This is very much useful in oil well applications. Ultrasonic measurements confirmed that temperature and pressure significantly influence hydration rates and viscosity changes. Their study highlights that increasing temperature quickens hydration but can lead to micro cracking due to thermal stresses.

Xie and Qian *et al.*[16] developed a numerical model with help of thermodynamic model and finite element analysis to predict the hydration heat of concrete. They integrate Fourier's heat conduction law, hydration kinetics, and the

Arrhenius equation to simulate temperature evolution. Experimental results confirm that model closely matches measured temperature data. Their findings show that higher cement content and Supplementary Cementitious Materials (SCMs) can significantly affect the hydration heat release.

The study of Nguyen-Tuan *et al.*[17] highlights the model's ability to capture phase transformations. Also shows to dissolution of binder phases, and formation of hydration products, including inner and outer C-S-H and Portlandite. The developed numerical model used level set method to simulate the microstructural evolution of cement hydration. The main focus of authors was on fibrous characteristics Calcium Silicate Hydrate (C-S-H). The model effectively computes volumetric phase changes.

Ahmed *et al,*[19] used 5 mathematical models such as full quadratic, non-linear, multi-linear, linear and interaction regression model to predict the compressive strength of cement paste. Large data set is used from previously published research works. They conclude that the model developed in this study can use by researchers and construction industry with high accuracy.

Kawan Ghafor *et al.*[20] collected over 1,000 datasets from the literature on the mechanical properties like compressive strength of mortar made by cement and modified with silica percentages ranging from 5% to 55%. The non-linear regression, modeling and statistical analysis is performed. The comparison is made between Vipula Nandan correlation and Hoek-Brown model to correlate the mechanical properties of mortar (sand + cement) modified with silica fume. Their study shows good connection between the compressive strength with flexural strength and tensile strength for mortar altered with silica fume.

Baoyu Ma *et al.*[21] derived a analytical model to predict elastic properties of hydrating cement paste, namely the prediction of percolation, hydration, and homogenization. Mineral composition and w/c ration considered in hydration model.

Y. Gao *et al.*[22] said elastic modulus is a fundamental parameter which controls the mechanical behavior of cement paste. X-ray calculated tomography images were used for to show structural features of cement paste. A two-level modeling procedure was executed in terms of a hybrid analytical-numerical algorithm. The results specify a good correlation between the modeling and the ultrasonic wave test.

O. Bernard *et al.*[23] proved in their study that Continuum micromechanics, combined with advanced cement chemistry hydration models, helps study the aging elasticity of cement-based materials. It requires only a few intrinsic material properties; normally they are same for all cement-based materials. The model includes 11 mix-design-specific parameters.

Mathematical model established by S. Tsivilis *et al*[25] they shown the importance of chemical-mineralogical and fineness. Also proved fineness is affecting the early strength chemical and mineralogical synthesis of the cement contributes to the strength development after 7 and 28 days.

4.0 Research Gap

Even though several ML and traditional models have been developed to forecast the mechanical and physical properties of cement and cement mortar, still some gaps remain. Most models created for limited datasets or specific environmental conditions and types of cements. Many of them are failing to capture complex relation between hydration kinetics and microstructure development. There is also lack of unified and scalable model that combine real time data from field. Limited studies are available; those would have compared the accuracy of ML models and traditional models.

5.0 Conclusion

This review paper combines the study of both machine learning models and traditional models for prediction of mechanical and physical properties of cement and cement mortar. Machine learning models like PINN-CHK, SVM-GA, and DNN-GANs have revealed excellent prediction accuracy by using limited dataset. Future research can work on robust, faster and accurate testing methods in the construction sector. The insights from this review aim to guide researchers and experts to understand the efficiency of different predictive models with their key findings.

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