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Machine Learning Approach for Optimization of Concrete Mixes with Supplementary Materials

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ABSTRACT

Durability of concrete has always been an important topic since many concrete failures or signs of failure result from exposure to severe service or environmental conditions. The Gulf region has a harsh metrological environment and is currently witnessing a wide urbanization development. Billions of dollars are being spent on reinforced concrete construction projects and their repair in this region. These projects will not only exert pressure on resources but will also require high-performance materials for long-lasting durability and efficient repair systems. This study investigates the optimization of concrete mix designs using machine learning techniques, specifically focusing on the interplay between Ground Granulated Blast Furnace Slag (GGBS), Micro silica content, and their effects on concrete water permeability and cost. A Random Forest Regressor was employed to model the complex relationships between these variables, revealing key insights into how varying proportions of GGBS and Micro silica influence the overall performance and economic feasibility of concrete mixes. The analysis identified an optimal mix containing 61.1% GGBS and 14 kg/m³ micro silica, which achieves a favorable balance between low water permeability (1.37 mm) and cost efficiency (49.5 USD/m³). The insights gained from the model can inform better material selection for mix designs, contributing to more durable and cost-effective concrete structures, reducing the need for costly repairs, and minimizing resource consumption in urban development projects.

1.Introduction

Concrete is the most used construction material with a worldwide annual production of 4.4 billion metric tons [1]. Concrete is subject to several forms of attacks including physical attack, chemical attack, sulfate attack, leaching and alkali aggregate reaction that may affect concrete durability [2]. Causes of defects in concrete structures can be due to structural deficiency resulting from errors in design, loading criteria, unexpected overloading, structural deficiency due to construction defects, damage due to fire, floods, earthquakes, cyclones, damage due to chemical attacks, damage due to marine environments and damage due to abrasion of granular materials. Various types of defects can be observed in hardened concrete surfaces including cracking, crazing, blistering, delamination, dusting, curling, efflorescence, scaling and spalling. Each type of concrete defect has a certain cause, cracks for example are formed because of different reasons such as insufficient curing, error in expansion and contraction joints, or the use of high slump concrete mix [3-4].

Public agencies are spending significantly on repairs and rapidly increasing proportions of their construction budgets for repairs and maintenance of existing concrete infrastructure. Moreover, many studies have developed advanced methods to repair and maintain concrete structures [5-7]

However, prevention is the best form of therapy, therefore optimizing concrete mix to achieve maximal durability is crucial to prevent future deterioration of structures. Enhanced compounds of concrete are highly reflected in the durability and service life of new structures which is not only important from an economical point of view; but also, directly affects sustainability. Improving concrete durability is crucial and needs more research to come up with optimized concrete mix designs. Neville [8] also mentioned that cases of outright failure or collapse caused by too low strength are extremely rare, while there are numerous cases of inadequate performance of concrete through a lack of durability. Consequently, durability is gaining more importance in modern design and optimizing concrete mixes to maximize durability.

Moreover, durability of materials incorporated into a repair shall be considered for individual repairs, as the overall durability of the repaired structure, and the interaction of the repair system with the structure is crucial to guarantee a sustainable and effective repair. The durability of materials incorporated into a repair depends on their ability to withstand the environment where they are installed and the compatibility between repair materials, the structure, and the surrounding environment including chemical, electrochemical, and physical behavior.

Micro silica has a great potential to increase the durability of concrete mixes. It is a byproduct of the silicon and ferrosilicon alloy production process. It consists of very fine particles with a high content of silicon dioxide (SiO_2) and has been extensively researched for its application in concrete. Micro silica enhances the compressive strength of concrete by filling the voids between cement particles and producing a denser microstructure. This effect is due to both the physical filling capability and the pozzolanic reaction of micro silica with calcium hydroxide, resulting in additional calcium silicate hydrate (C-S-H) formation [9,10]. Filling the voids can have major reduction in permeability which is reflected in enhancing concrete mixes durability [11,12]. The durability of concrete is markedly improved by the incorporation of micro silica, particularly in terms of resistance to chemical attack and permeability, especially in environments exposed to aggressive chemicals like chlorides and sulfates. The addition of Micro silica to concrete mixes has great potential to enhance its durability and mechanical properties especially in the Arabian Gulf where it has to endure hot weather and harsh conditions.

Samarai et al. [13] explored the durability challenges of reinforced concrete in the Arabian Gulf, where the harsh environmental conditions—such as high temperatures, humidity fluctuations, and salt-laden atmospheres—accelerate deterioration. The study focused on the performance of concrete under hot weather, utilizing tensile specimens to examine cracking tendencies and non-destructive testing for compressive strength evaluation. The methodology included testing five concrete mixes, incorporating supplementary materials like micro silica, GGBS, and metakaolin. Results indicated that adding micro silica significantly enhanced concrete's durability, particularly by reducing permeability and cracking. For instance, mixes with low water-to-cement ratios (0.32-0.38) exhibited about a 20-40% increase in crack width under high temperatures (up to 50°C) for low-slump concrete, whereas high-slump mixes saw a reduction in crack widths by 30-40%. These findings emphasize the importance of optimizing mix designs for the Gulf region's severe climate to ensure long-term concrete performance.

The precise percentage of micro silica required in concrete mixes remains a topic of active research. Nowadays, with the availability of advanced machine learning technologies, this challenge can be effectively addressed, enabling more accurate and efficient optimization of mix proportions. This claim is supported by several research studies that have been used to optimize concrete mix design compressive strength and other properties with machine learning [14-17].

Kumar et al. [18] investigated the effectiveness of various machine learning models in predicting the permeability and half-cell potentiometer test readings of hybrid concrete containing different percentages of blast furnace slag and fly ash, particularly when exposed to a chloride-rich environment. The study assessed the permeability and compressive strength of the hybrid concrete using 36 cast cubes and conducted half-cell potentiometer tests on the beam samples. Three machine learning models—AdaBoost, random forest, and XGBoost—were used to predict the permeability values. Among these, AdaBoost showed the highest accuracy, demonstrating strong correlations between observed and predicted values. The study's findings contribute to simplifying the process of corrosion detection in concrete and support the development of more accurate and robust corrosion monitoring systems.

Shaynfar et al. [19] studied the impact of rising global temperatures on concrete durability, particularly the damage caused by sulfate ions in coastal and offshore structures. The study involved testing concrete specimens containing silica fume and nano silica, exposed to a sodium sulfate solution at different temperatures 24.85°C, 29.85°C, and 34.85°C) over 360 days, with drying-wetting cycles. The study monitored mass changes, sulfate concentration, and compressive strength, while also using SEM-EDS, XRD, and TGA to analyze the microstructure of the concrete. Machine learning, specifically the Multi-Layer Perceptron (MLP) algorithm, was employed to predict sulfate ion penetration. The results showed that higher temperatures increased sulfate penetration, but this effect was mitigated by higher percentages of supplementary cementitious materials. The MLP model demonstrated high accuracy, with R^2 values of 0.9821 and 0.9741 for specific mixes, indicating strong predictive performance.

Mane et al. [20] aimed to estimate the impact strength and chloride permeability of concrete made with cementitious waste ingredients, with partial replacement of natural fine aggregates by artificial sand. Using MATLAB, a model was created, and cylindrical samples were tested for impact strength and chloride permeability. An artificial neural network (ANN) was developed and trained on 400 experimental results (80% for training and 20% for testing). The ANN model provided precise predictions of the impact strength and chloride permeability of concrete mixed with industrial waste materials and artificial sand, with a percentage error between 0% and 5%. The study's findings demonstrate that substituting cement and natural aggregates with these materials can reduce environmental impact and promote the use of sustainable concrete.

Cao [21] used machine learning to predict the porosity of high-performance concrete containing supplementary cementitious materials. A database of 240 records with 74 unique concrete mixtures was used, featuring variables like water/cement ratio, fly ash, slag, aggregate content, superplasticizers, and curing conditions. The results indicate that gradient boosting trees, particularly XGBoost, provide the most accurate predictions, with an R^2 of 0.9770, MAPE of 2.97%, and RMSE of 0.431. This data-driven approach outperforms traditional models by effectively handling time-dependent hydration and achieving higher accuracy. Key predictors of porosity include curing duration in days, water/binder ratio, and aggregate content.

Kazimi and Gholampour [22] study addressed the challenge of reducing concrete permeability to enhance durability, specifically by preventing chloride ion penetration. It explores the use of self-compacting concrete (SCC) incorporating supplementary cementitious materials like fly ash and silica fumes. Traditional methods like the rapid chloride permeability test (RCPT) are time-consuming and costly. To improve efficiency, the study proposes three predictive models combining artificial neural networks (ANN) with metaheuristic optimization techniques: particle swarm optimization (PSO), ant colony optimization (ACO), and biogeography-based optimization (BBO). The ANN-BBO model showed the highest accuracy in predicting chloride ion penetration resistance, outperforming the other models. The study also identified sample temperature during testing as the most critical factor influencing

RCPT results, contributing 25% to the model's accuracy.

Nevertheless, the optimization of micro-silica and GGBS content in concrete using machine learning, specifically focusing on its impact on water permeability, remains unexplored. This paper aims to fill this gap by employing machine learning techniques to study and optimize the concentration of micro-silica and GGBS in concrete repair mixes for improved water permeability and water absorption resistance.

2.Materials and Methods

2.1 Concrete Mixes and Water Permeability Test

All concrete mixtures used in this study were prepared using a typical Type I cement, which meets the requirements of ASTM C150. Furthermore, the aggregates primarily consisted of crushed stone, dune sand, and crushed sand, all sourced locally. Table 1 summarizes the data recorded as inputs and outputs for the study.

Table 1 Dataset Parameters

Data Type	Parameters	Unit
Input	Unconfined Compressive Strength	MPa
	GGBS Content	%
	Micro silica Content	kg/m^3
Output	Total Cost	USD/m^3
	Water Absorption	mm

The water absorption for each mix was determined using the ASTM C642 methodology. Data was collected for 8 mixes and a total of 223 samples. Table 2 summarizes the average values of each property obtained for each mix.

Table 2 Average Values for Each Mix Property in the Study

Mixes	Concrete Strength (N/mm^2)	GGBS (%)	MS (kg/m^3)	Water Absorption (mm)
Mix A	40	50	0	1.44
Mix B	40	50	12.9	1.11
Mix C	40	70	0	1.37
Mix D	40	70	15	1.25
Mix E	45	50	0	1.19
Mix F	45	50	21.5	1.17
Mix G	45	70	0	1.21
Mix H	45	70	22.5	1.14

2.2 Cost Optimization through Machine Learning

This study aims to provide insights into the most cost-effective combinations of GGBS and Micro silica, contributing to the development of durable and economical concrete solutions. The main outputs are the water absorption and the associated costs of each concrete mix. These outputs were then analyzed using machine learning models, specifically Random Forest Regressors, to predict water permeability and optimize the mix design for minimal permeability at the lowest possible cost.

MATLAB R2021b software was used to perform the Random Forest Regressor machine learning model. Random Forest Regressor is a robust technique designed to improve predictive accuracy and control overfitting. It operates by averaging the predictions from multiple decision trees, each trained on a random subset of the data.

The analysis begins with bootstrap generating (D_b) from a given training set $D_b=\{(x_1,y_1),(x_2,y_2),\dots (x_n,y_n)\}$, then for each bootstrap sample a decision tree (T_b) is created. At each node, a random subset of features (N_b) is selected, and the best split is chosen based on minimizing the mean squared error (MSE):

$$MSE=(1/N)\sum_{i=1}^{N}(y_i-\hat{y}_i)^2$$

Where (y_i) is the actual value and $(\hat{y}_i)$ is the predicted value from the tree. The final prediction $(\hat{y})$ for a new input (x) is obtained by averaging the predictions from all B trees:

$$\hat{y}=(1/B)\sum_{b=1}^{B}T_b(x)$$

The model was trained on the collected dataset, which was split into training (80%) and testing (20%) sets to evaluate the model's performance. The Mean Squared Error (MSE) was used as the primary metric to assess the model's performance in predicting water permeability and cost. A multi-objective optimization approach was applied to identify the optimal combination of GGBS and Micro silica that minimizes both water permeability and cost. Fig. 1 presents the

Random Forest Regressor framework used in this study.

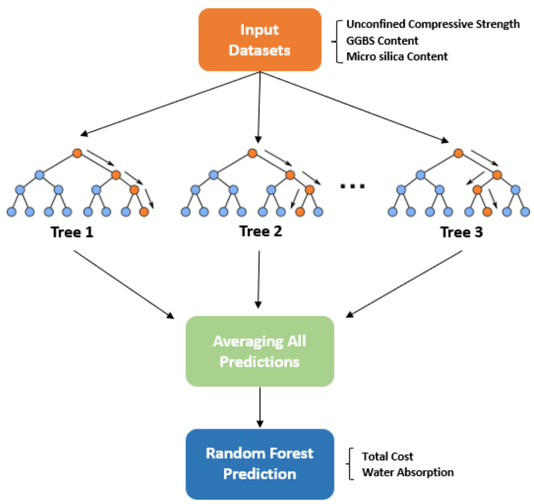

Fig. 1 Random Forest Regressor framework for predicting cost and water absorption

3. Discussion of Results

3.1 Water Permeability Testing

The experiments carried out on assessing durability from the water absorption test are summarized below. The different variables assessed included concrete strength as an indication of quality control and mineral admixtures, including Ground Granulated Blast Furnace Slag (GGBS) and micro-silica (MS). The analysis illustrated the relationship between different concrete mixes, their respective water absorption rates, and the strength classifications (C45/20 and C40/20), GGBS percentage and Micro silica (MS) content. It is evident that mixes with higher Micro silica content generally exhibit lower water absorption rates. This trend is consistent across both strength classifications (C45/20 and C40/20), highlighting the significant role of Micro silica in reducing permeability in concrete.

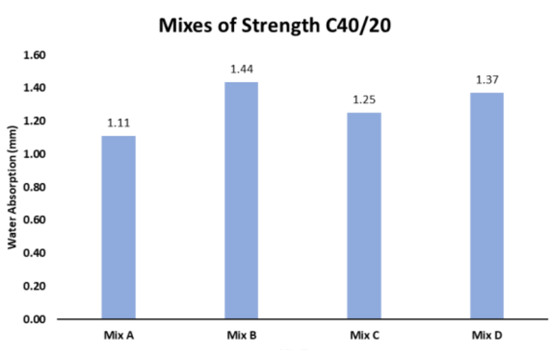

Fig. 2 Water Absorption for C45/20 Concrete Mixes with Varying Micro silica Content

Fig 2. shows that Mix A (GGBS 50%, MS 0 kg/m³) has a water absorption of 1.44 mm. When Micro silica is added in Mix B (GGBS 50%, MS 12.9 kg/m³), the absorption decreases significantly to 1.11 mm. For higher GGBS content, Mix C (GGBS 70%, MS 0 kg/m³) shows 1.37 mm absorption, while Mix D (GGBS 70%, MS 15 kg/m³) reduces it to 1.25 mm.

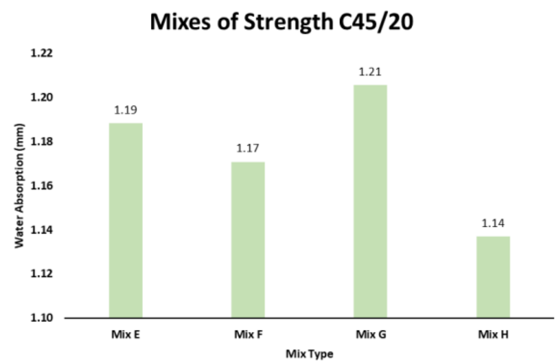

Fig. 3 Water Absorption for C40/20 Concrete Mixes with Varying Micro silica Content

Fig 3. shows that Mix E (GGBS 50%, MS 0 kg/m³) has a water absorption of 1.19 mm, which is slightly reduced in Mix F (GGBS 50%, MS 21.5 kg/m³) to 1.17 mm, illustrating the beneficial impact of adding Micro silica. Similarly, Mix G (GGBS 70%, MS 0 kg/m³) shows a higher water absorption rate of 1.21 mm compared to Mix H (GGBS 70%, MS 22.5 kg/m³), which has the lowest water absorption at 1.14 mm.

While these findings demonstrates a clear advantage of GGBS and MS still it emphasizes the complex interplay between these additives and the resulting water absorption properties of the concrete. The significant variations in water absorption between different mixes, even within the same strength classification, highlight the necessity for a further analysis to optimize concrete performance.

The complexity of such analysis is where machine learning becomes highly advantageous. Moreover, cost optimization is another crucial aspect that is difficult to address in traditional analysis. Machine learning models, such as the Random Forest Regressor, can capture these complex interactions by analyzing large datasets and providing insights into the most cost-effective combinations of materials to achieve the desired performance.

3.2 Random Forest Regressor Analysis

The Random Forest models were utilized for their predictive capabilities concerning water permeability and cost optimization for the input featured, which included GGBS percentage and Micro silica content. The models demonstrated significant predictive accuracy. A low Mean Squared Error (MSE) values were obtained during the modeling reflecting high accuracy. MSE for water permeability prediction was 0.034 and 0.0012 for the cost prediction. This is attributable to the relatively straightforward relationship between the material costs and the mix design parameters, which the model was able to capture effectively.

Using these predictions, the optimization process identified a mix composition that minimizes both cost and water permeability. The optimal mix was found to consist of 61.1% GGBS and 14 kg/m³ of Micro silica, with a predicted water permeability of 1.37 mm and a cost of 49.5 USD/m³. This mix was selected as it effectively balances the goals of reducing water permeability, which is crucial for concrete durability, and maintaining cost efficiency.

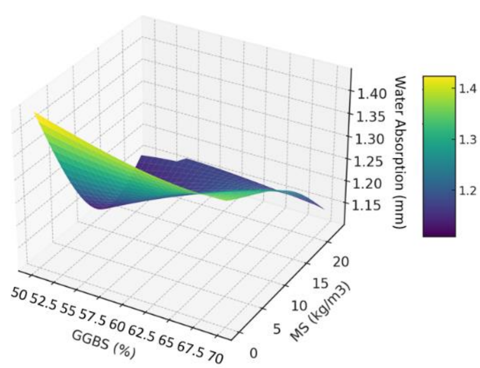

Fig. 1 3D Surface-Plot between MS, GGBS and Water Absorption

Fig 4 shows the relationship between Ground Granulated Blast Furnace Slag (GGBS) percentage, Micro silica (MS) content, and water absorption in concrete mixes. The relationship was thoroughly analyzed using both machine learning models and 3D surface plotting. The analysis revealed that increasing Micro silica content consistently leads to a reduction in water absorption, particularly when combined with higher percentages of GGBS. This finding aligns with the observed trends in the data, where mixes with 61.1% GGBS and approximately 14 kg/m³ of Micro silica were identified as optimal for achieving low water permeability while maintaining cost efficiency. The 3D surface plot further confirmed these results, showing a clear downward trend in water absorption with increasing Micro silica and GGBS levels. These consistent observations confirm the robustness of the model's predictions and highlight the importance of optimizing both GGBS and micro silica in concrete mix designs to enhance durability and cost-effectiveness.

Fig. 5 shows a contour plot illustrating the relationship between Ground Granulated Blast Furnace Slag (GGBS) percentage, Micro silica content, and the associated costs of concrete mixes. The color gradient on the plot represents the cost per cubic meter, with cooler tones indicating lower costs and warmer tones indicating higher costs. The analysis reveals that costs increase significantly with higher Micro silica content, particularly when GGBS levels are kept constant or increased. This is consistent with the known expense associated with Micro silica as an additive. The plot also highlights a cost-efficient zone at approximately 61.1% GGBS and moderate Micro silica levels, where the transition to higher costs is less pronounced. This zone aligns well with the identified optimal mix for balancing low water permeability and cost-effectiveness. These observations confirm that while adding Micro silica improves performance, its contribution to overall costs must be carefully managed to achieve economically viable concrete mixes. The contour plot serves as a valuable tool in visualizing the cost implications of varying material compositions, reinforcing the utility of machine learning in optimizing concrete mix designs.

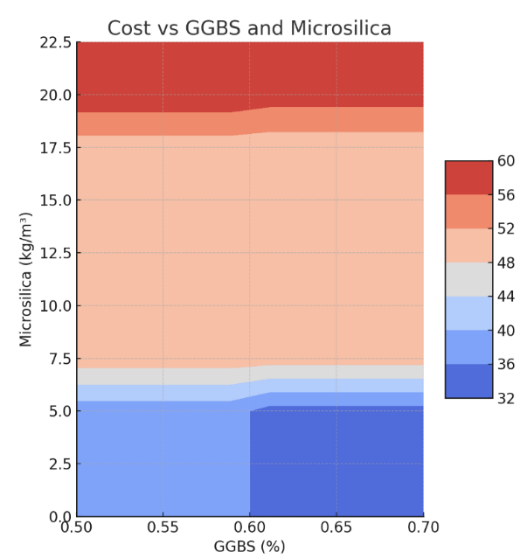

Fig. 5 Contour plot illustrating the relationship between GGBS percentage, Micro silica content, and concrete mix costs

4. Conclusion

This research successfully demonstrates the application of machine learning, particularly Random Forest Regressor, in optimizing concrete mix designs by balancing water permeability and cost. The study identified that a concrete mix containing 61.1% GGBS and 14 kg/m³ of Microsilica achieves optimal performance, minimizing water permeability while maintaining cost-effectiveness. The integration of machine learning allowed for a nuanced analysis of the non-linear relationships between GGBS, Microsilica, and their combined effects on concrete properties. The findings were further corroborated by 3D surface and contour plots, which provided visual confirmation of the model's predictions. These insights highlight the potential of machine learning in advancing concrete technology, offering a data-driven approach to material optimization that can significantly improve the sustainability and durability of concrete structures. Future research can build on these results by exploring additional variables and incorporating real-time data to further refine the predictive models and enhance the robustness of the mix design process.

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