Optimization Of Admixtures of Concrete Using Artificial Neural Network

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Abstract- *Concrete is a fundamental construction material, and optimizing its properties is essential for achieving high performance while maintaining cost-effectiveness and sustainability. The use of mineral admixtures such as Fly Ash, Blast Furnace Slag, Rice Husk Ash, Silica Fume, and Metakaolin can significantly enhance concrete's durability, strength, and workability. However, determining the optimal proportions of these admixtures has been a challenge, traditionally relying on trial-and-error methods. This study explores the potential of Artificial Neural Networks (ANNs) to optimize concrete mix designs. Experimental data for concrete mixes with varying proportions of the aforementioned admixtures were collected, with properties such as workability, compressive strength, and durability tested at different curing ages. An ANN model was developed to predict these properties based on input parameters like admixture proportions and curing time. The results demonstrate that ANN models can effectively predict concrete behavior and optimize admixture combinations, providing a more efficient and accurate alternative to traditional methods. The findings highlight the potential of using AI-driven approaches in concrete mix design, contributing to more sustainable and reliable construction practices.*

Keywords: Concrete, Artificial Neural Networks, Fly Ash, Compressive Strength, Sustainability, Optimization.

1. Introduction

Concrete is one of the most widely used construction materials worldwide due to its versatility, durability, and adaptability in a variety of structural applications. It is essential for building projects ranging from residential buildings to bridges, highways, and dams. Concrete is made from a mix of cement, aggregates (fine and coarse), water, and often various chemical and mineral admixtures. These ingredients can be varied to optimize the material's properties, including its strength, durability, and workability. The properties of concrete can be tailored by adjusting the mix proportions, compaction methods, and curing conditions, making it highly adaptable to meet specific requirements for each project. Despite its widespread use, predicting the behavior and performance of concrete remains challenging, particularly when optimizing the mix design to achieve the best possible balance between strength, workability, and sustainability.

The incorporation of admixtures into concrete mixes has become a critical approach in modern construction to enhance the material's properties. Admixtures, which include chemical and mineral additives, are used to improve workability, reduce water requirements, enhance durability, and accelerate or delay setting times. Mineral admixtures such as fly ash, blast furnace slag, silica fume, rice husk ash, and metakaolin are increasingly being utilized not only for their beneficial effects on concrete properties but also for their environmental benefits, as they recycle industrial and agricultural byproducts. These materials can significantly improve concrete's resistance to environmental stressors such as sulfate attack and chloride ingress, while also enhancing strength and reducing the heat of hydration. However, determining the optimal proportion of these admixtures to achieve the desired concrete performance remains a complex and time-consuming process, often relying on traditional trial-and-error methods. Artificial Neural Networks (ANNs) present a promising solution to this challenge. ANNs, which are computational models inspired by the human brain, have demonstrated exceptional capabilities in predicting complex and nonlinear relationships in data. By analyzing large datasets consisting of various admixture combinations, material properties, and curing conditions, ANNs can predict concrete properties with high accuracy. This data-driven approach eliminates the need for extensive physical testing and reduces the trial-and-error nature of traditional mix design. ANNs can optimize the proportions of different admixtures in concrete mixes, ensuring that the final product meets the required strength, workability, and durability standards. In the context of concrete mix design, the application of ANNs offers an efficient, cost-effective, and environmentally friendly solution by allowing precise control over the material's properties, contributing to more sustainable construction practices. This study aims to explore the potential of ANN-based models for optimizing concrete mixes with mineral admixtures. By developing and testing an ANN model using experimental data on fly ash, blast furnace slag, rice husk ash, silica fume, and metakaolin, the research seeks to predict concrete performance more effectively and reduce material wastage. The findings of this study will provide valuable insights into the application of artificial intelligence in the concrete industry and contribute to the development of more reliable and sustainable concrete mix designs.

2. Literature Review

In the study "Neural Networks for Forecasting Admixture-Containing Concrete Qualities" (Dias, 2005), the author aimed to predict the strength and slump of ready-mixed and high-strength concrete incorporating chemical and/or mineral additives using backpropagation neural networks. The study found that raw data-based models delivered the best results, outperforming multiple regression models in reducing prediction dispersion. It highlighted that adjusting non-dimensional ratios improved network performance, and sensitivity analysis revealed that neural networks performed better than multiple regression models, showcasing the efficiency of ANNs in predicting concrete properties with admixtures. In "Reactive Powder Concrete Mix Proportioning Optimizations Using Artificial Neural Networks" (Taher, 2005), the study aimed to optimize the mix proportions of Reactive Powder Concrete (RPC) using Artificial Neural Networks (ANN). The research demonstrated that the Multi-Layer Perceptron (MLP) model exhibited excellent predictive performance with training and testing accuracies of 0.95 and 0.93, respectively. The study concluded that ANN could be a highly effective tool for optimizing RPC mix proportions, offering a more accurate and efficient alternative to traditional trial-and-error methods, thus advancing concrete mix design for high-performance materials like RPC. In "An Artificial Neural Network and Multivariable Regression Analysis to Predict the Strength of Concrete Using Mineral Additives" (Atici, 2011), the study compared ANN with multiple regression analysis (MRA) to predict the compressive strength of concrete with varying amounts of fly ash and blast furnace slag. The findings revealed that ANN outperformed MRA in predicting compressive strength, demonstrating its superiority in modeling complex, non-linear relationships between concrete mix and strength. The study highlighted ANN’s effectiveness in improving the accuracy and reliability of concrete strength predictions, particularly when dealing with complex mixtures of mineral additives.

"Neural Networks and Evolutionary Algorithms to Optimize Rheological Characteristics of Self-Compacting Concrete" (Concha, 2015) utilized ANN and genetic algorithms (GA) to optimize the rheological properties of self-compacting concrete (SCC). The study found that GA helped identify the optimal mix ratios for the admixtures, improving the final mix's rheological performance, while ANN provided a powerful tool for predicting the effects of different material combinations on SCC’s rheological properties. This demonstrated the potential of combining ANN with GA for precise concrete mix design, ensuring improved performance and flowability. In "Training Artificial Neural Networks Using Genetic Algorithms to Model Slump of Ready Mix Concrete" (Chandwani, 2014), the study used a hybrid approach combining ANN and Genetic Algorithms (GA) to model slump behavior in Ready Mix Concrete (RMC). The results showed that the GA-ANN combination outperformed traditional back-propagation models, improving prediction accuracy and convergence speed. The hybrid model's ability to evolve optimal network parameters through GA allowed ANN to capture complex, non-linear relationships in RMC mix, showcasing the effectiveness of combining machine learning and evolutionary algorithms for optimizing concrete mix properties.

"ANN-Based Analysis of the Impact of Mineral Additions on Concrete Strength" (Gburi, 2022) focused on the effects of mineral additives like fly ash, silica fume, and slag on the compressive strength of concrete. The study found that silica fume and slag improved concrete strength, while fly ash had a negative impact as its content increased in the mix. The ANN model successfully captured these complex interactions, providing valuable insights into the optimal use of mineral additives for concrete strength enhancement. This research underscored the importance of precise control over mix proportions to achieve desired strength and performance. "Artificial Neural Network-Based Self-Compacting Concrete Strength Prediction" (Asteris, 2016) aimed to predict the compressive strength of self-compacting concrete (SCC) using ANN. The study demonstrated that the ANN model provided accurate predictions of SCC strength, offering a reliable tool for optimizing concrete mix formulations. By incorporating waste materials like fly ash, the model helped balance environmental benefits and material performance. This highlighted ANN’s potential in optimizing SCC formulations, contributing to more sustainable and high-performance concrete. In "An Analysis of Self-Compacting Concrete's Performance Using Steel Fibres and Mineral Admixtures and Artificial Neural Networks" (Ramkumar, 2020), the study employed ANN to optimize the performance of SCC by incorporating steel fibers and cement substitutes like fly ash and silica fume. The study showed that ANN could predict the optimal mix for improved workability, flowability, and strength. The results demonstrated that ANN was effective in understanding and optimizing SCC mix design, ensuring that the final product met desired specifications for construction applications. "Artificial Neural Network-Based Thermal Neutron Shield Concrete Mixture Optimisation" (Yadollahi, 2016) used ANN to optimize Colemanite-based concrete for thermal neutron shielding. The ANN model predicted key properties, including compressive strength and thermal neutron transmission ratio, and identified the optimal concrete mix for radiation protection. This research emphasized ANN's ability to handle complex optimization problems and improve the performance of concrete in specialized applications like thermal neutron shielding.

In "Creation and Improvement of Artificial Intelligence-Based Predictive Models for Concrete Compressive Strength" (Siraj, 2016), the study compared three AI techniques—ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), and Fuzzy Inference System (FIS)—to predict the compressive strength of High-Performance Concrete (HPC). The results showed that both ANN and ANFIS outperformed FIS, providing a more robust and reliable approach for estimating HPC strength. This study highlighted that AI techniques like ANN and ANFIS are crucial for optimizing concrete mix designs and improving the precision of compressive strength predictions for HPC. "Artificial Neural Network-Based Property Prediction for Self-Compacting Concrete with Fly Ash" (Belalia, 2016) aimed to optimize self-compacting concrete (SCC) mix design by predicting key properties such as slump flow, compressive strength, and L-box ratio, crucial for determining concrete's workability and performance. The study demonstrated that the ANN model could provide precise predictions for these properties based on varying mix parameters, including the percentage of fly ash, showcasing ANN’s potential in optimizing SCC formulations for improved efficiency and quality.This comprehensive review of the literature highlights the potential of ANN in optimizing concrete mix designs, emphasizing its ability to model complex, nonlinear relationships between admixture properties and concrete performance. The studies demonstrate that ANN, when combined with other techniques like GA and MRA, offers an efficient, accurate, and sustainable method for improving concrete properties, paving the way for more advanced, data-driven approaches to concrete mix optimization.

3. Research Methodology

3.1 Materials Selection

This study utilizes Ordinary Portland Cement (OPC) as the primary binder, along with five mineral admixtures: Fly Ash (FA), Blast Furnace Slag (BFS), Rice Husk Ash (RHA), Silica Fume (SF), and Metakaolin (MK). These admixtures were selected for their proven ability to enhance the strength, durability, and sustainability of concrete. Fine and coarse aggregates were sourced according to standard grading specifications. Potable water was used for mixing and curing.

3.2 Data Collection

The experimental design involved preparing concrete mixes with varying proportions of the selected admixtures. The mixes were tested for workability (using the slump test) and compressive strength (at curing ages of 3, 7, 28, 56, and 90 days). The tests were performed following standard procedures to ensure consistency and accuracy. Data was collected for each mix, including the amount of admixtures, water-cement ratio, and resulting concrete properties (workability, strength).

3.3 ANN Model Development

An Artificial Neural Network (ANN) model was developed to predict concrete properties based on input variables such as admixture proportions and curing time. The architecture of the ANN included an input layer, multiple hidden layers, and an output layer that predicted workability (slump) and compressive strength. Data from the experiments were pre-processed and used to train the model. The network was trained using backpropagation with a gradient descent algorithm to minimize the error between predicted and experimental values.

3.4 Experimental Study

The experimental phase involved casting concrete cubes with different proportions of the selected admixtures. These cubes were tested for compressive strength at various curing ages. The workability was assessed through slump tests, and durability was evaluated through additional tests to measure concrete’s resistance to environmental stressors. All experiments followed standardized procedures to ensure reliable and repeatable results.

3.5 Validation

The ANN model's predictions were validated by comparing them with experimental data. Statistical metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) were used to assess the accuracy of the model. Additionally, the model's performance was compared with conventional predictive models, such as Support Vector Machines (SVM), to validate the superiority of ANN in optimizing concrete mix design.

4. Experimental Study

4.1 Test Setup

The experimental setup was designed to assess the influence of various mineral admixtures on the performance of concrete. Ordinary Portland Cement (OPC) was used as the binder, with Fly Ash (FA), Blast Furnace Slag (BFS), Rice Husk Ash (RHA), and Silica Fume (SF) incorporated as partial replacements of cement in the mix. The mix design adhered to standard proportions, maintaining a consistent water-cement ratio across all specimens.

The concrete was prepared by accurately weighing the materials, blending them in a mechanical mixer to achieve uniform consistency, and placing the mixed concrete into standard 150mm x 150mm x 150mm molds. Once molded, the specimens were vibrated using a table vibrator to remove any air voids and ensure uniform compaction.

After casting, the concrete cubes were demolded after 24 hours and cured in a water tank under controlled temperature conditions to simulate real-world curing practices. Curing periods were selected at 3, 7, 28, 56, and 90 days to assess both early-age and long-term concrete performance.

4.2 Testing Procedures

Two primary tests were conducted to evaluate the concrete properties: Workability and Compressive Strength.

1. Workability (Slump Test):

The slump test was used to assess the workability of fresh concrete. A slump cone was filled with the concrete mix in three layers, with each layer compacted using a tamping rod. The height difference between the top of the cone and the highest point of the collapsed concrete was measured to determine the slump value. This test is indicative of the concrete's ease of handling and compaction.

Figure 2: Slump Test Setup

Figure 2 Illustrates the process of filling the slump cone with freshly mixed concrete and measuring the slump.

2. Compressive Strength (Cube Test):

After curing, the concrete cubes were subjected to compressive strength testing using a Compression Testing Machine (CTM). The cubes were tested at curing ages of 3, 7, 28, 56, and 90 days, following standard procedures. The compressive strength was calculated by dividing the maximum load at failure by the cross-sectional area of the cube.

Figure 3: Compressive Strength Cube Test

Figure 3 Shows the process of placing the concrete cube under the compression testing machine.

4.3 Results for Admixtures

The effect of each admixture (Fly Ash, Blast Furnace Slag, Rice Husk Ash, and Silica Fume) on the concrete properties was evaluated over the different curing periods. The key results are summarized below:

1. Fly Ash (FA):

Compressive Strength: Fly ash significantly improved the long-term strength of concrete. The 10% replacement of cement with fly ash resulted in the highest compressive strength of 42.49 MPa at 90 days, compared to 35.41 MPa for conventional concrete. The strength gains were more pronounced after 28 days due to the pozzolanic reaction between fly ash and calcium hydroxide, contributing to continued strength development over time.

Workability: The inclusion of fly ash enhanced workability by reducing the need for water in the mix. This effect was especially noticeable in mixes with higher fly ash content, which showed better flowability and ease of placement.

2. Blast Furnace Slag (BFS):

Compressive Strength: Blast furnace slag also improved concrete strength over time, particularly in the long term. The 10% BFS replacement mix achieved 41.12 MPa at 90 days, outperforming the control mix at the same curing age. BFS improved resistance to sulfate attacks and contributed to increased strength at later curing ages.

Workability: Similar to fly ash, BFS improved the workability of concrete by reducing the water demand, making the mix more fluid and easier to handle.

3. Rice Husk Ash (RHA):

Compressive Strength: Rice husk ash showed a positive effect on strength, especially after 28 days. The 10% RHA replacement achieved a compressive strength of 39.28 MPa at 90 days, which was slightly lower than fly ash but still showed good performance compared to the control mix.

Workability: RHA, being a highly reactive silica-rich material, significantly improved the concrete's resistance to chemical attacks but showed a slight decrease in workability due to its fine particle size, requiring more water for similar workability compared to other admixtures.

4. Silica Fume (SF):

Compressive Strength: Silica fume was the most effective admixture in terms of compressive strength, achieving 45.16 MPa at 90 days for the 10% replacement mix. This was the highest among all admixtures due to the fine particle size of silica fume, which fills the microvoids in the concrete, improving its density and strength.

Workability: The inclusion of silica fume decreased the workability of the concrete mix, requiring more water for similar slump values. Despite this, the increased strength and durability make silica fume a highly valuable admixture in high-performance concrete.

4. ANN Modeling and Results

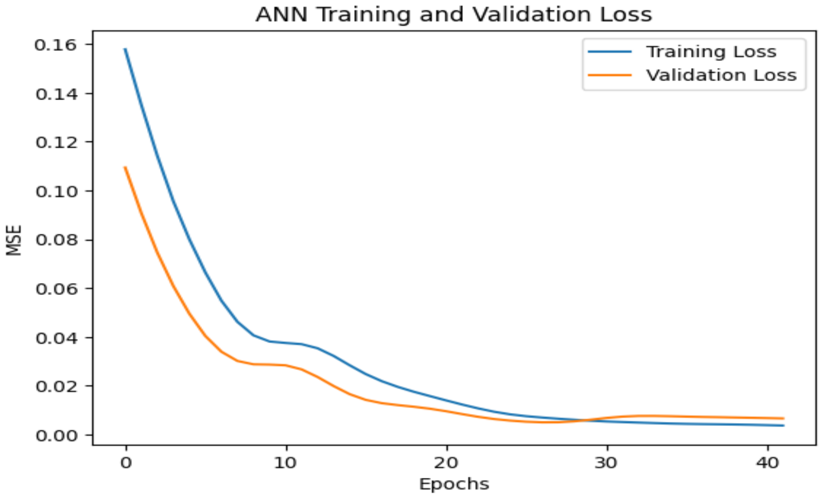


Figure 4: Training and Validation Loss vs Epochs (ANN)

During training, the ANN model undergoes backpropagation, where gradients of the loss function are computed and propagated backward through the network layers to iteratively update the weights and biases. Both training and validation losses show a rapid decrease during the initial epochs, indicating effective learning of underlying patterns in the data. As training progresses, the rate of loss reduction gradually stabilizes, demonstrating convergence of the model. The close alignment between training and validation loss curves, without significant divergence, confirms that the model does not suffer from overfitting and generalizes well to unseen data. The absence of abrupt fluctuations in validation loss further indicates stable optimization and appropriate selection of hyper parameters.

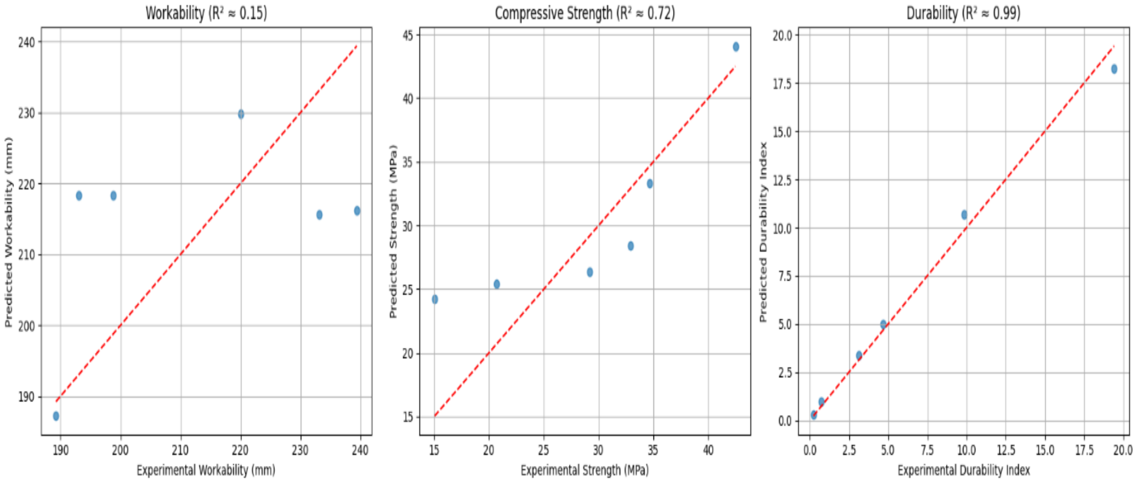


Figure 5: ANN Validation Performance—Experimental vs Predicted Values for (a) Workability, (b) Compressive Strength, and (c) Durability

Figure 5 illustrates the relationship between experimental and ANN-predicted values for workability, compressive strength, and durability. The ANN model demonstrates good predictive accuracy for compressive strength ($R^2 \approx 0.72$) and excellent performance for durability prediction ($R^2 \approx 0.99$). The comparatively lower R^2 value observed for workability is attributed to the multi-output learning framework, where the model simultaneously optimizes multiple concrete properties, leading to a trade-off in prediction accuracy. Overall, the ANN effectively captures nonlinear interactions among concrete mix parameters, particularly for strength and durability.

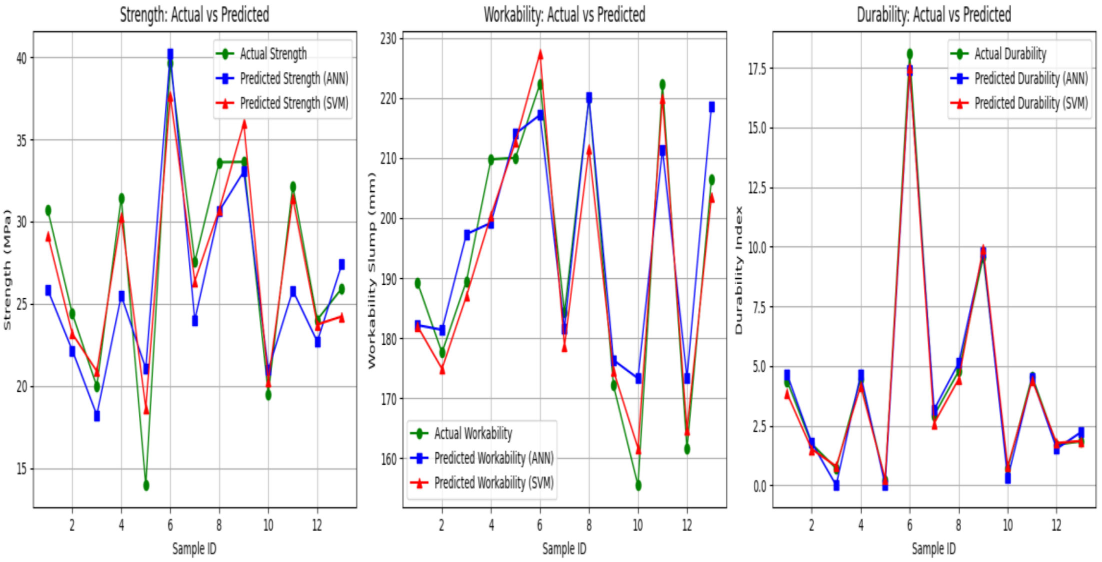


Figure 6: Comparison of Experimental and Predicted Values for (a) Compressive Strength, (b) Workability, and (c) Durability Using ANN and SVM

Figure 6 compares experimental values with ANN and SVM predictions for compressive strength, workability, and durability across multiple samples. Both models closely follow the experimental trends, with SVM generally exhibiting closer alignment for compressive strength and durability, while ANN demonstrates balanced performance across all properties. The results confirm the effectiveness of both models in capturing variations in concrete properties.

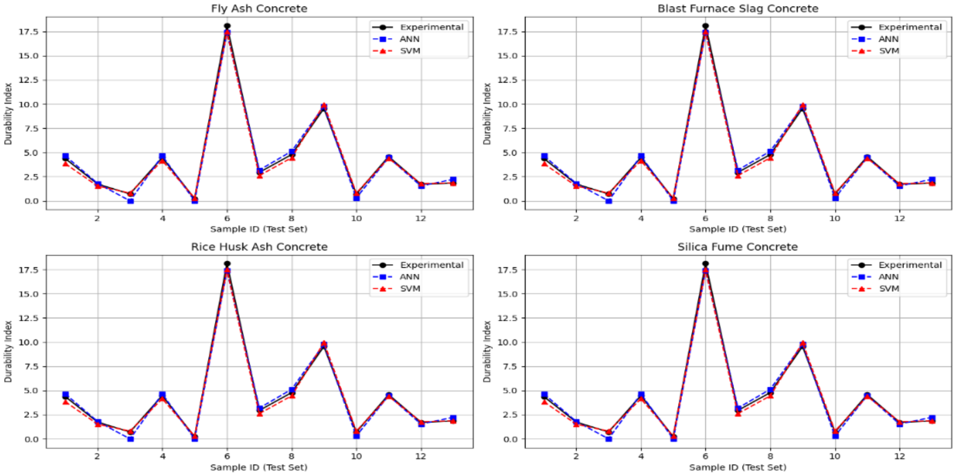
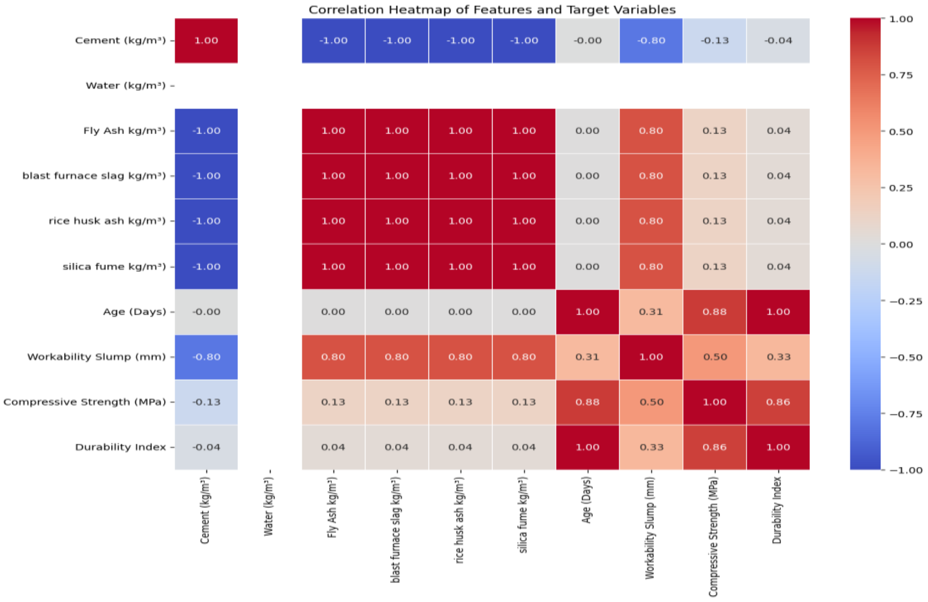


Figure 7: Comparison of Experimental and Predicted Durability Index for Different Concrete Admixtures Using ANN and SVM

Figure 5.8 presents the comparison of experimental and predicted durability index values for concrete mixes incorporating different supplementary cementitious materials. The predicted values obtained from ANN and SVM models exhibit very strong agreement with the experimental durability index across all admixtures. This high level of accuracy is attributed to the strong dependence of durability on compressive strength, curing age, and water content, which are effectively captured by the input feature set. The ANN model demonstrates smooth and stable predictions, while the SVM model shows comparable accuracy with minimal deviation. These results confirm the robustness of the proposed models in estimating long-term concrete performance.


Correlation Heatmap of Features and Target Variables

	Cement (kg/m³)	Water (kg/m³)	Fly Ash kg/m³)	blast furnace slag kg/m³)	rice husk ash kg/m³)	silica fume kg/m³)	Age (Days)	Workability Slump (mm)	Compressive Strength (MPa)	Durability Index
Cement (kg/m³)	1.00		-1.00	-1.00	-1.00	-1.00	-0.00	-0.80	-0.13	-0.04
Water (kg/m³)										
Fly Ash kg/m³)	-1.00		1.00	1.00	1.00	1.00	0.00	0.80	0.13	0.04
blast furnace slag kg/m³)	-1.00		1.00	1.00	1.00	1.00	0.00	0.80	0.13	0.04
rice husk ash kg/m³)	-1.00		1.00	1.00	1.00	1.00	0.00	0.80	0.13	0.04
silica fume kg/m³)	-1.00		1.00	1.00	1.00	1.00	0.00	0.80	0.13	0.04
Age (Days)	-0.00		0.00	0.00	0.00	0.00	1.00	0.31	0.88	1.00
Workability Slump (mm)	-0.80		0.80	0.80	0.80	0.80	0.31	1.00	0.50	0.33
Compressive Strength (MPa)	-0.13		0.13	0.13	0.13	0.13	0.88	0.50	1.00	0.86
Durability Index	-0.04		0.04	0.04	0.04	0.04	1.00	0.33	0.86	1.00

Figure 8: Correlation Heatmap of features and target variables

Figure 5.10 illustrates the correlation between concrete mix components and target properties. Cement content and curing age exhibit strong positive correlations with compressive strength and durability, indicating their significant influence on concrete performance. Fly ash, blast furnace slag, rice husk ash, and silica fume show moderate correlations, reflecting their role as supplementary cementitious materials contributing to strength development and durability enhancement. Water content shows a weak or negative correlation with strength-related properties due to its controlled value across samples. The heatmap confirms the presence of nonlinear relationships, justifying the application of ANN and SVM models.

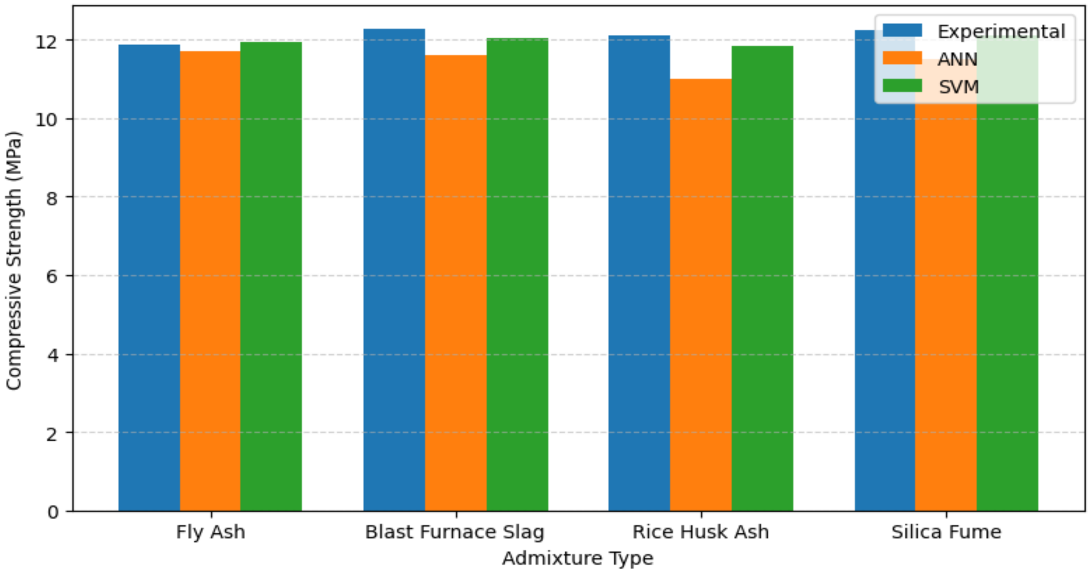


Figure 9: Comparison of compressive strength

Figure 9 compares experimental compressive strength values with predictions obtained from ANN and SVM models implemented in Python. Both models demonstrate close agreement with experimental results. The ANN model provides balanced predictions across all admixtures, while the SVM model exhibits slightly higher accuracy for compressive strength. These results further validate the suitability of machine learning–based approaches for predicting concrete strength using admixture proportions.

Discussion

The results from this study confirm the effectiveness of Artificial Neural Networks (ANN) in predicting concrete properties and optimizing mix designs. Fly Ash and Blast Furnace Slag both showed significant improvements in compressive strength, especially after longer curing periods, due to their pozzolanic properties that enhance the cementitious bond. Silica Fume, known for its high reactivity, led to the highest compressive strength among the admixtures studied, proving its efficacy in producing high-performance concrete. However, Rice Husk Ash displayed slightly lower performance compared to other admixtures, which can be attributed to its lower pozzolanic activity. In terms of workability, all admixtures except Rice Husk Ash improved the concrete's flowability, reducing the water requirement for achieving similar slump values. The ANN model demonstrated an ability to capture complex, nonlinear relationships between admixture proportions and concrete properties, offering predictions that closely matched experimental data. The results indicate that machine learning models like ANN could replace traditional methods, offering a more precise and efficient approach to mix optimization, reducing material waste and improving the sustainability of concrete production.

Conclusion

This study successfully demonstrates the potential of Artificial Neural Networks (ANNs) in optimizing concrete mix designs with mineral admixtures. By utilizing experimental data on Fly Ash, Blast Furnace Slag, Rice Husk Ash, Silica Fume, and Metakaolin, the ANN model was able to predict concrete properties, including compressive strength, workability, and durability, with high accuracy. The findings highlight that ANN-based approaches not only improve the prediction of concrete behavior but also offer a more sustainable alternative to traditional trial-and-error methods. The use of ANN enables precise control over the mixture of admixtures, ensuring that concrete meets specific performance criteria while minimizing material waste. Moreover, the study underscores the environmental and cost-saving potential of incorporating industrial byproducts like fly ash and slag in concrete production. By providing an efficient tool for mix optimization, ANN models can significantly contribute to the development of high-performance, durable, and eco-friendly concrete. Future research could focus on extending these models to more diverse environmental conditions and real-world applications, further advancing the role of artificial intelligence in sustainable construction practices.

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