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Enhancing Concrete Performance: Experimental And Neural Network-Based Optimization Of Admixtures For Improved Workability And Flexural Strength

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ABSTRACT

This study explores enhancing concrete performance through experimental and Artificial Neural Network (ANN) optimization techniques. Concrete mixes incorporating five different admixtures—fly ash, blast furnace slag, rice husk ash, silica fume, and eggshell powder—were prepared and analyzed. The methodology involved a comprehensive approach: first, concrete mix designs were developed based on standard calculations to achieve target mean strength and appropriate water-cement ratios. Experimental batches of concrete were then cast and cured, with properties such as workability and flexural strength assessed through slump cone tests and Universal Testing Machines over various curing periods. Concurrently, an ANN model was constructed to predict concrete performance based on the proportions of admixtures. The ANN model was designed with an input layer for admixture proportions, hidden layers for learning complex patterns, and an output layer for predicting workability and flexural strength. The model was trained using the experimental data and validated with a separate dataset to evaluate its predictive accuracy. Although the ANN model faced challenges, with high error metrics and weak correlation between experimental and predicted values, it provided insights into optimal admixture proportions. The study highlights the effectiveness of combining experimental research with neural network-based optimization to develop high-performance and sustainable concrete formulations, advancing the field of concrete technology.

Keywords: Concrete Performance, Admixtures, Fly Ash, Egg Shell Powder, Artificial Neural Networks (ANN), Workability, Flex al Strength.

I INTRODUCTION

Concrete is a critical material in modern construction, known for its versatility and strength. However, achieving optimal performance in terms of workability and flexural strength remains a challenge due to the complex interactions between various admixtures and mix components[1], [2]. Traditional methods of concrete mix optimization often involve empirical approaches, which can be time-consuming and may not fully capture the intricate relationships between mix parameters[3]. Recent advancements in computational techniques, particularly the use of neural networks, offer promising alternatives for optimizing concrete performance[4]. Neural networks, with their ability to model complex, non-linear relationships, can analyze vast datasets to predict the impact of different admixture combinations on concrete properties[5], [6]. These models can enhance our understanding of how factors such as cement content, water-to-cement ratio, and the inclusion of mineral additives influence workability and strength[7]. Experimental studies complement these computational approaches by providing empirical data that validate and refine neural network predictions[8]. Integrating these methods allows for a more precise optimization process, leading to improved concrete formulations that achieve better performance while potentially reducing costs and environmental impacts[9], [10].

Admixtures play a crucial role in enhancing concrete properties by modifying its behavior and performance[11]. These additives can improve workability, allowing for easier mixing and placement of concrete[12]. They also reduce water content, leading to higher strength and durability[13]. Additionally, certain admixtures accelerate setting time, which is beneficial in speeding up construction schedules or in cold weather conditions[14]. Optimizing admixtures in concrete using neural network-based methods offers significant advancements in improving workability and flexural strength[15]. Neural networks can analyze complex interactions between different admixtures and their effects on concrete properties, allowing for precise adjustments to enhance workability, which facilitates easier mixing, handling, and placement[16]. Additionally, these models can optimize formulations to boost flexural strength, ensuring greater load-bearing capacity and durability[17].
This paper explores how experimental methods, alongside advanced neural network models, can refine the use of admixtures to significantly enhance both workability and flexural strength of concrete[18]. By integrating these methodologies, the study aims to develop more effective concrete mixtures that facilitate easier handling [19]and placement while achieving superior load-bearing capacity[20]. The synergy of practical experimentation and predictive modeling offers a comprehensive solution for optimizing concrete formulations, ultimately leading to improved performance and durability in construction applications[21], [22]. This research aims to explore and leverage both experimental[23] and neural network-based techniques to advance concrete technology, addressing current limitations and pushing the boundaries of what is achievable in concrete performance[24].

II LITERATURE REVIEW

This research explores methods to enhance concrete performance through experimental and neural network-based optimization of admixtures. Existing studies focus on traditional optimization techniques and the integration of advanced computational models to improve workability and flexural strength, highlighting the need for innovative approaches in concrete technology**.**
W.P.S. Dias et.al (2001), utilized backpropagation neural networks to predict the strength and slump of ready-mixed and high-strength concrete incorporating chemical admixtures and mineral additives. The study found that models based on raw data provided superior results compared to those using non-dimensional ratios. The raw data models effectively captured fundamental rules and second-order effects governing concrete strength, while models based on non-dimensional ratios showed limitations, such as inaccurate sensitivity analyses and undue weightage to incidental ratios. The neural network models demonstrated reduced prediction scatter compared to multiple regression models and better performance in strength prediction, though the accuracy for slump prediction was lower[1]. **Joaquın Abellan Garcıaa et.al (2017),** developed four analytical models based on artificial neural networks (ANN) to predict the compressive strengths at 1-day, 7-day, and 28-day intervals, as well as the slump flow of ultra-high-performance concrete (UHPC). This study utilized recycled glass powder, fluid catalytic cracking residue (FCC), and various particle sizes of limestone powder as partial replacements for Portland cement and silica fume. The ANN models demonstrated accurate predictions with root mean square errors (RMSE) of 2.400 MPa, 2.638 MPa, 2.064 MPa, and 7.245 mm for compressive strengths and slump flow, respectively. The models were validated using K-Fold cross-validation with four partitions, achieving strong correlation coefficients (R^2) of 0.982, 0.976, 0.960, and 0.983[25]. **Chang Sun et.al (2023),** investigated the optimization of ultra-high-performance concrete (UHPC) mix proportions to balance performance with cost and carbon emissions. UHPC is known for its superior strength and durability, making it ideal for large-span and ultrahigh-rise buildings. However, its extensive use of cementitious materials leads to high costs and carbon emissions, restricting its wider application. The study employed machine-learning algorithms to predict UHPC properties such as compressive strength, flexural strength, fluidity, and shrinkage. Among the algorithms, XGBoost showed the best performance with a mean absolute percentage error (MAPE) below 5% and an R^2 above 0.9. The research analyzed 50,000 random UHPC mixes to calculate their cost and carbon emissions per unit volume. **I.-C. Yeh et.al (1998),** explored the use of artificial neural networks (ANN) to predict the compressive strength of high-performance concrete (HPC), a complex material influenced by various mix ingredients beyond the water-to-cement ratio. Laboratory-produced HPC trial batches demonstrated satisfactory results. The study concluded that ANN-based models outperform traditional regression analysis models in accuracy. ANN, a family of parallel architectures that use interconnected artificial neurons, provides a rapid and effective way to calculate node outputs based on trained weights. The coefficient of determination (R^2) was used to test the accuracy of the trained network, indicating how well independent variables account for the dependent variable. The study highlights that ANN models are not only more precise but also convenient for numerical experiments, allowing for detailed analysis of how different variables affect concrete strength, such as age or water-to-binder ratio[26]. **Seyed Adel Ahmadi Hosseini et.al (2019),** explored the efficacy of the Deep Mixing Technique (DMT) for improving weak soils, particularly in the South-west of Iran. The study involved both in-situ and laboratory tests to assess the impact of DMT on soil strength. A parametric analysis examined factors such as cement content, water-cement ratio, curing time, and plasticity index (PI), with 192 different conditions analyzed through 3D plotting and artificial neural networks (ANNs). Results highlighted the critical role of the water-cement ratio, revealing that ANN models provided accurate predictions for soil strength under various admixture conditions, with a coefficient of determination greater than 0.85. Key findings included that shear

strength increased with cement content and curing time, but the rate varied with soil type. A reduced plasticity index and optimal water-cement ratio also enhanced strength. The study demonstrated that 3D plots and ANN are effective for optimizing DMT processes, making ANN a powerful tool for predicting and improving soil strength in field applications[27]. **Gökhan Kaplan (2019)** explored the use of mineral admixtures like fly ash, blast-furnace slag, and limestone powder in concrete production for sustainability. Hardened concrete properties were examined under different curing conditions and water/cement (w/c) ratios. While slag cement showed lower early-age strength, it improved significantly by the 90th day. The study found that standard curing offered the best compressive strength, while higher w/c ratios negatively impacted properties. ANN was used to estimate compressive strength with high accuracy, achieving correlation coefficients close to 1 for training, validation, and testing datasets[28]. **Kasperkiewicz et al. (1995)** were among the pioneers in employing ANN for predicting high-performance concrete (HPC) strength. Their study, published in the Journal of Computing in Civil Engineering, demonstrated the potential of neural networks to model complex relationships between the variables influencing concrete strength. The authors underscored the accuracy and efficiency of ANN in handling the non-linear characteristics of HPC, setting a foundation for future research in this area. **Noorzaei et al. (2007)** further advanced the application of ANN by developing models to predict concrete compressive strength. Their study, published in the International Journal of Engineering and Technology, showcased the robustness of ANN in predicting concrete strength across different mix designs and curing conditions. The authors emphasized the potential of ANN to serve as a reliable tool for engineers in designing and evaluating concrete structures[29].**Ozturan et al. (2008)** compared various concrete strength prediction techniques, including traditional statistical methods and ANN. Their findings, published in the Building Research Journal, indicated that ANN outperformed other techniques in terms of accuracy and reliability. This study underscored the superiority of ANN in modeling the complex relationships between concrete components and their resulting strength, reinforcing its adoption in civil engineering practices.In 2009, Rasa1 et al. examined the use of ANN to predict the density and compressive strength of concrete containing silica fume. Published in the Civil Engineering journal, their research highlighted the effectiveness of ANN in handling the additional complexities introduced by silica fume. The study demonstrated that ANN could accurately predict the properties of modified concrete mixtures, providing engineers with a powerful tool for optimizing concrete performance[30].

Mohammad and Mohammad (2009) discussed considerations in producing high-strength concrete in their paper published in the Journal of Civil Engineering. They explored how ANN could aid in addressing the challenges associated with high-strength concrete production. Their findings emphasized the role of ANN in enhancing the understanding and control of factors affecting concrete strength, contributing to the development of more robust and durable concrete structures[31]. **Subasi (2009)** focused on predicting the mechanical properties of cement containing Class C fly ash using ANN and regression techniques. His research, published in the Scientific Research and Essay journal, demonstrated that ANN provided superior predictive accuracy compared to traditional regression methods. Subasi's work highlighted the advantages of ANN in incorporating complex interactions between fly ash and cement components, leading to better performance predictions. **Deka and Diwate (2011)** modeled the compressive strength of ready-mix concrete using soft computing techniques, including ANN. Their study, published in the International Journal of Earth Sciences and Engineering, showcased the practical benefits of ANN in predicting ready-mix concrete strength. The authors emphasized the efficiency of ANN in processing large datasets and its ability to deliver accurate predictions, making it an invaluable tool for the ready-mix concrete industry. **Amer hasan taher et.al (2018),** aims to optimize the mix proportions of Reactive Powder Concrete (RPC) mixtures by Artificial Neural Networks (ANN) technique. Ninety-nine sets of RPC mixes with their results from six different sources are used to check the reliability of the model. The values of compressive strength (Fc), Splitting Tensile Strength (Fsp) and Flexural strength (Fr) were specified as the input parameters. The values of sand to powder ratio (S\P), water to powder ratio (W\P) and volume of steel fiber (Vf) are computed and specified as the output parameters. (Fc) model with an architecture Multi Layers Perceptron (MLP) 3-40-1 had (0.95) training performance, (0.4%) training error, (0.93) testing performance and (0.4%) testing error. Fsp model with MLP 4-13-1 has (0.99) training performance, (0.014%) training error, (0.99) testing performance and (0.011%) testing errors. The primary predicting model has the architecture MLP 3-14-3. It also has training performance, training error, testing performance and testing error values of (0.96), (0.8%), (0.93), and (1.2%) respectively. All of the ANN models show very good percentages of correlation between target and output values with very low values of error, and high percentage of matching between targets and outputs, and no clear trend to overestimation or underestimation.

2.1 Research gap

This research identifies several gaps in the current literature on neural network-based optimization for concrete performance. Despite advancements in predicting strength and workability, integration with practical mix design constraints remains insufficient. There is a need for more comprehensive studies on real-world applications, including cost and environmental impacts, as well as a better understanding of material variability. Additionally, while various optimization techniques for concrete and soil have been explored, a unified approach across different concrete types and conditions is lacking.

III RESEARCH METHODOLOGY

The methodology of this study involves a comprehensive approach to enhancing the performance of concrete using various admixtures. The experimental phase focuses on optimizing concrete mix designs by incorporating five distinct admixtures: fly ash, blast furnace slag, rice husk ash, silica fume, and egg shell powder. Conventional concrete mixes and those with 2% cement replacement by each admixture are prepared. Key properties, such as workability and flexural strength, are evaluated using standardized tests. To achieve a deeper understanding and precise optimization, an artificial neural network model is employed to predict and analyze the impacts of these admixtures on concrete performance. This dual approach of experimental investigation and neural network-based optimization aims to identify the optimal proportions and combinations of admixtures, enhancing concrete's workability and flexural strength while promoting sustainability.

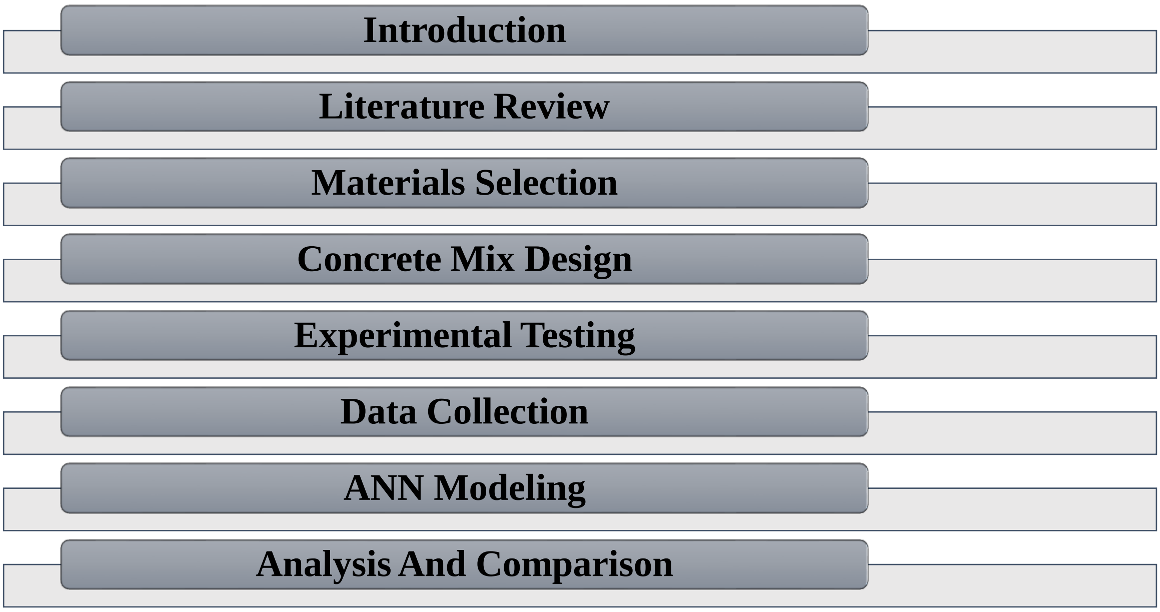

Fig 1: Flowchart of Methodology

3.1 Materials Selection

Five admixtures were selected for their potential to improve concrete properties: fly ash, blast furnace slag, rice husk ash, silica fume, and egg shell powder.

3.2 Concrete Mix Design

The calculations for a sample M30 concrete mix design with the following assumptions:

- Specific Gravity of Cement (G_c) = 3.15
- Specific Gravity of Coarse Aggregate (G_ca) = 2.8
- Specific Gravity of Fine Aggregate (G_fa) = 2.7
- Maximum Size of Coarse Aggregate = 20mm
- Workability (Slump) = 75mm

1. Target Mean Strength:

Target Strength for Mix Proportioning

In order that not more than the specified proportion of test results are likely to fall below the characteristic strength, the concrete mix has to be proportioned for higher target mean compressive strength $f_{ck.}$ The margin over characteristic strength is given h) the following relation:

$$f'_m = f'_c + k \times S$$

fm′= Target mean strength
fc′ = Specified characteristic strength
k = Statistical constant based on the desired confidence level (for a 95% confidence level, k is typically 1.65)
S = Standard deviation of the compressive strength of concrete

- f'm = 30 + (1.65 * 5) = 38.25 N/mm²

2. Water-Cement Ratio (w/c):

The water content of concrete is influenced by a number of factors, such as aggregate size, aggregate shape, aggregate texture, workability, water-cement ratio, cement and other supplementary cementitious material type and content, chemical admixture and environmental conditions. An increase in aggregates size, a reduction in water-cement ratio and slump, and use of rounded aggregate and water reducing admixtures will reduce the water demand. On the other hand increased temperature, cement content, slump, water-cement ratio, aggregate angularity and a decrease in the proportion of the coarse aggregate to fine aggregate will increase water demand.

The quantity of maximum mixing water per unit volume of concrete may be determined from Table 2. The water content in Table 2 is for angular coarse aggregate and for 25 to 50 mm slump range. The water estimate in Table 2 can be reduced by approximately 10 kg for sub-angular aggregates, 20 kg for gravel with some crushed particles and 25 kg for rounded gravel to produce same workability. For the desired workability (otherthan 25 to 50 mm slump range), the required watercontent may be established by trial or an increase by about 3 percent for every additional 25 mm slump or alternatively by use of chemical admixtures conforming to IS 9103. This illustrates the need for trial batch testing of local materials as each aggregate source is different and can influence concrete properties differently. Water reducing admixtures or superplasticizing admixtures usually decrease water content by 5 to 10 percent and 20 percent and above respectively at appropriate dosages.

Table 1: Maximum Water Content per Cubic Metre of Concrete for Nominal Maximum Size of Aggregate (Clauses 4.2. A-5 and B-5)

Nominal Maximum Size of Aggregate (mm)	Maximum Water Content (liters)
10	208
20	186
40	165

- w/c = 0.42 (assumed based on moderate workability)

3. Water Content:

From Table 5 of IS 456, maximum water-cement ratio = 0.45. Based on experience, adopt water-cement ratio as 0.42. 0.42 < 0.45, hence O.K

- Based on IS 10262:2009 Table 2 (or site experience), estimated water content (w) = 180 liters/m³

From Table 2, maximum water content for 20 mm aggregate =186 litre (for 25 to 50 mm slump range)
Estimated water content for 100 mm slump = 186+ (6 X 186/100)
= 197 litre

4. Cement Content (C):

Water-cement ratio= 0.42
Cement content = 197/0.42
$C = w / (w/c) = 197$ liters/m³ / 0.42 = 469.047 kg/m³

Table 2: Minimum Cement Content, Maximum Water-Cement Ratio and Minimum Grade of Concrete for different Exposures with Normal Weight Aggregates of 20 mm Nominal Maximum Size (Clause» 6.1.2, 8.2.4.1 and 9.1.2)

Exposure	Plain Concrete			Reinforced Concrete		
	Minimum Cement Content (kg/m³)	Maximum Water-Cement Ratio	Minimum Grade of Concrete	Minimum Cement Content (kg/m³)	Maximum Water-Cement Ratio	Minimum Grade of Concrete
Mild	220	0.60	-	300	0.55	M20
Moderate	240	0.60	M15	300	0.50	M25
Severe	250	0.50	M20	320	0.45	M30
Very Severe	260	0.45	M20	340	0.45	M35
Extreme	280	0.40	M25	360	0.40	M40

From Table 5 of IS 456, minimum cement content for 'severe' exposure condition = 320 kg/m3
469.047 > 320 kg/m3 hence, O.K.

5. Volume of Coarse Aggregate (V_ca):

Table 3 of IS 10262-2009 specifies the proportions of coarse and fine aggregates required to mix concrete. The workability of concrete depends on the coarse aggregates. Further, the volume of coarse aggregates in a unit volume of concrete depends on the fine aggregates' nominal maximum size and grading zone. In certain cases, where the concrete requires greater workability, the proportion of coarse aggregates may be reduced, provided that the strength of the concrete conforms to IS 456.

Table 3 Volume of Coarse Aggregate per Unit Volume of Total Aggregate for Different Zones of Fine Aggregate (Clauses 4.4, A-7 and B-7)

Nominal Maximum Size of Aggregate (mm)	Volume of Coarse Aggregate per Unit Volume of Total Aggregate for Different Zones of Fine Aggregate			
	Zone IV	Zone III	Zone II	Zone I
10	0.50	0.48	0.46	0.44
20	0.66	0.64	0.62	0.60
40	0.75	0.73	0.71	0.69

From Table 3 of (IS 10262:2009) Volume of coarse aggregate corresponding to 20 mm size aggregate and fine aggregate (Zone II) for water-cement ratio of 0.50 =0.66.
In the present case water-cement ratio is 0.42. Therefore, volume of coarse aggregate is required to be increased to decrease the fine aggregate content. As the water-cement ratio is lower by 0.06. The proportion of volume of coarse aggregate is increased by 0.02 (at the rate of -/+ 0.01 for every ± 0.05 change in water-cement ratio).
Therefore, corrected proportion of volume of coarse aggregate for the water-cement ratio of 0.42 = 0.64
NOTE – In case the coarse aggregate is not angular one, then also volume of coarse aggregate may be required to be increased suitably based on experience & Site conditions.
For pumpable concrete these values should be reduced up to 10%. Therefore, volume of coarse aggregate =0.64 x 0.9 =0.576 m3
Volume of fine aggregate content = 1 – 0.576= 0.424.

6. Volume of concrete

Volume of concrete = 1 m3

7. Volume of cement

$$\frac{\text{Mass of cement}}{\text{Specific gravity of cement}} \times \frac{1}{1\,000}$$

= 469.047/3.15 X 1/1000
=0.1489 m3

8. Volume of water

$$\frac{\text{Mass of water}}{\text{Specific gravity of water}} \times \frac{1}{1\,000}$$

= (197)/1 X (1/1000)
= 0.197 m3

1. Volume of chemical admixture (superplasticizer) (@ 2.0 percent by mass of cementitious material)

= (Mass of chemical admixture/ Specific gravity of admixture) X (1/1000)

9. Volume of all in aggregate

= 1-(0.1489+0.197)
= 0.6541 m3

10. Mass of coarse aggregate

=e x Volume of coarse aggregate x Specific gravity of coarse aggregate x I 000
= 0.6541 X 0.576 X 2.8 X 1000
= 1054.9325 kg

11. Mass of fine aggregate

=e x Volume of coarse aggregate x Specific gravity of coarse aggregate x I 000
= 0.6541 X 0.424 X 2.7 X 1000
= 748.813 kg

12. Summary

Cement = 469.047 kg/m3
Water = 197 kg/m3
Fine aggregate = 748.813 kg/m3
Coarse aggregate 1054.9325 kg/m3
Chemical admixture = - kg/m3
Water-cement ratio = 0.42

3.3 Experimental study

This study investigated the optimization of concrete performance through the use of five distinct admixtures: fly ash, blast furnace slag, rice husk ash, silica fume, and egg shell powder. Each of these admixtures was selected for its unique properties and potential to enhance concrete characteristics such as workability and flexural strength.

Fly ash, a byproduct of coal combustion in power plants, is known for its pozzolanic properties, which contribute to improved durability and reduced permeability of concrete. Blast furnace slag, a byproduct of iron production, offers benefits such as enhanced strength and resistance to aggressive environmental conditions. Rice husk ash, derived from the controlled burning of rice husks, is rich in silica and helps improve the mechanical properties and longevity of concrete. Silica fume, an ultrafine powder produced during the manufacturing of silicon and ferrosilicon alloys, is highly reactive and significantly boosts concrete's compressive and flexural strength. Lastly, egg shell powder, an innovative and sustainable admixture, provides a source of calcium carbonate that can improve the setting time and strength of concrete. The experimental phase involved preparing conventional concrete and concrete mixes where 2% of the cement was replaced with each of the selected admixtures. Through a combination of these experimental techniques and artificial neural network modeling, study aimed to identify the optimal proportions and synergies of these admixtures to enhance the workability and flexural strength of concrete. This holistic approach not only provides a deeper understanding of the individual and collective impacts of these admixtures but also offers a pathway to developing more sustainable and high-performance concrete formulations.

Table 4: Specific gravity of admixtures

Specific gravity	**Values**	**Reference**
fly ash	2.288	https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=a674fda96e04cc8bb98430cc0025c26e4d8a3db8
blast furnace slag	2.9	https://www.wellesu.com/10.1016/B978-0-08-102156-9.00012-2
silica fume	2.65	https://www.researchgate.net/profile/Kirtikanta-Sahoo/publication/318026424_Mechanical_properties_of_silica_fume_concrete_designed_as_per_construction_practice/links/59567a6645851523cc91e1f6/Mechanical-properties-of-silica-fume-concrete-designed-as-per-construction-practice.pdf
rice husk ash	1.55	https://d1wqtxts1xzle7.cloudfront.net/43880886/STRUCTURAL_PROPERTIES_OF_RICE_HUSK_ASH_C20160319-11265-otgoiw-libre.pdf?1458373367=&response-content-disposition=inline%3B+filename%3DStructural_Properties_of_Rice_Husk_Ash_C.pdf&Expires=1722080616&Signature=IQRBexsxJCC5~NnYsoexlFbn9nyWa9~3zpJBE3WIaHTUvWgqn1Vwz41GX907q~3fz5ZOk-etSiXGmhTraarp-i6SfLcJ9VytHPxz6IPH73jeXGwratK0xO48TWb8on9lELxeiVnz5aWUjlCKLG-qaTho9J2CyzzWC~Zfz2Wjniftnhk5F8zrvjdst~BcxRyxaBwhWeSpEIWQeeq4fX9VU9I4Gr1FeJciMC7RDeyOLPSyanD5sHoENshYtXvQiQcEHy9rBzD7bb70GEzLVQoMGOVLLboHsJbySL0zoFcDJU-UgEzwFQfPWOZ~FOyDaWtt4TJQh1ipOpkdTAV8DABotw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA
Egg shell powder	2.66	https://www.wellesu.com/10.1016/j.jobe.2020.101583

3.3.1 Sample calculation:

Mass of admixture = percentage replacement X cement volume

= 2% X 469.047

= 9.38858 kg

Volume of admixture= = (Mass of chemical admixture/ Specific gravity of admixture) X (1/1000)

For fly ash

= (9.388/2.288) X (1/1000)

= 0.0041034 kg/m3

Table 5: Volume of admixture

Volume of admixture					
	fly ash	blast furnace slag	silica fume	rice husk ash	egg shell powder
2%	0.0041034	0.00323744	0.0035429	0.006057	0.0035295

Volume of all in aggregate= 1- (volume of admixture + volume of cement + volume of water)

= 1-(0.004103+0.14902494+0.19716)

= 0.649711656 kg/m^3

Mass of Coarse Aggregate = =Volume of all in aggregate x Volume of coarse aggregate x Specific gravity of coarse aggregate x 1000
= 0.649711656 X 0.576 X 2.8 X 1000
= 1047.854959 kg/m3
Mass of Fine Aggregate = =Volume of all in aggregate x Volume of fine aggregate x Specific gravity of coarse aggregate x 1000
= 0.649711656 X 0.424 X 2.7 X 1000
= 743.7899042 kg/m3

Table 6: Summary of all aggregate calculations

Volume of all in aggregate					
	fly ash	blast furnace slag	silica fume	rice husk ash	egg shell powder
2%	0.649711656	0.650577615	0.650272196	0.64775791	0.65028552
Mass of Coarse Aggregate					
	fly ash	blast furnace slag	silica fume	rice husk ash	egg shell powder
2%	1047.854959	1049.251578	1048.758998	1044.70395	1048.78048
Mass of Fine Aggregate					
	fly ash	blast furnace slag	silica fume	rice husk ash	egg shell powder
2%	743.7899042	744.781254	744.4316103	741.553253	744.446858

3.4 Data Collection
Workability and flexural strength data were recorded for each concrete mix and curing period to analyze the effects of admixtures.

3.5 ANN Model Development
The development of the Artificial Neural Network (ANN) model begins with data preparation, where experimental data is organized into input and output variables. Input variables include admixture proportions, while output variables are workability (e.g., slump) and flexural strength. The next step involves designing the ANN architecture, which includes an input layer corresponding to the number of input variables, one or more hidden layers for feature extraction and representation, and an output layer representing the predicted workability and flexural strength. During the training phase, the ANN model is trained using the prepared experimental data.

Equations
1. Neuron Activation:

$$a_j = f\left(\sum_i w_{ij} x_i + b_j\right)$$

2. Output Layer:

$$y_k = f\left(\sum_j w_{jk} a_j + b_k\right)$$

3.Loss Function

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

3.6 Analysis and Comparison

Experimental results were compared with neural network predictions to evaluate model accuracy and determine optimal admixture proportions for enhanced concrete properties.

IV RESULT AND DISCUSSION

The results of this study provide a detailed analysis of the impact of various admixtures on the performance of concrete over different curing periods. The inclusion of fly ash, blast furnace slag, rice husk ash, silica fume, and egg shell powder significantly improved the workability and flexural strength of concrete. The experimental data, collected through tests conducted at 3, 7, 14, 21, 28, 56, and 90 days, highlight the progressive enhancement in concrete properties. Despite variations, all admixtures contributed to superior performance compared to conventional concrete. However, neural network predictions exhibited a weak correlation with experimental results, suggesting a need for model refinement.

Results

In this study casting of concrete cubes measuring 15x15x15 cm to evaluate the effects of the admixtures. The cubes were cured for various durations of 3, 7, 14, 21, 28, 56, and 90 days to observe the progression of strength and other relevant properties over time. After the designated curing periods, the cubes were tested to determine their workability and flexural strength. The results indicated significant improvements in concrete performance due to the inclusion of the admixtures, with notable variations observed at different curing stages. The data collected from these tests provide a comprehensive understanding of how each admixture impacts the concrete's properties over time, highlighting the potential for optimized concrete formulations in practical applications.

In this study, this machine was employed to evaluate the flexural strength of concrete specimens. The UTM is capable of applying controlled loads to the concrete samples, allowing for precise measurement of their flexural properties. The flexural test involves placing the concrete specimen on two supports and applying a load at the center until failure occurs. This setup helps in determining the concrete's ability to resist bending and cracking under load, which is critical for structural applications. The data obtained from these tests were crucial in analyzing the effects of different admixtures on the flexural strength of the concrete samples cured over various durations. The machine's versatility and precision ensured reliable and accurate results, contributing to the overall findings of this research on optimizing concrete performance with different admixtures.

The image depicts the setup for a slump cone test, a standard method used to assess the workability of fresh concrete. The test involves filling a truncated cone-shaped mold with concrete in three layers, each tamped 25 times with a tamping rod to ensure compaction. The cone is then carefully lifted vertically, allowing the concrete to slump. The height difference between the top of the mold and the top of the slumped concrete is measured to determine the slump value, which indicates the concrete's workability. A higher slump value suggests a more workable mix, while a lower value indicates a stiffer mix. In this study, the slump cone test was performed on various concrete mixes with different admixtures, such as fly ash, blast furnace slag, rice husk ash, silica fume, and egg shell powder. This test helped us evaluate the impact of these admixtures on the workability of concrete over different curing periods. The results provided critical insights into the suitability and performance of each admixture in enhancing the workability of concrete.

Table 7: Flexural strength results

	Average flexural Strength (N/mm2)						
Type of concrete	3 days	7 days	14 days	21 days	28 days	56 days	90 days
Conventional concrete	4.900722	5.047744	5.341787	5.63583	5.63583	5.748547	5.921003
2% replacement of concrete of fly ash	5.390794	5.552518	5.875966	6.199413	6.199413	6.323402	6.513104
2% replacement of concrete of blast furnace slag	6.984702	7.118514	7.693466	8.116959	8.116959	8.279298	8.527677
2% replacement of concrete of silica fume	7.88939	8.126072	8.599435	9.072799	9.072799	9.254255	9.531882
2% replacement of concrete of rice husk ash	8.678329	8.938679	9.459379	9.980079	9.980079	10.17968	10.48507
2% replacement of concrete of egg shell powder	9.632945	9.921934	10.49991	11.07789	11.07789	11.29944	11.63843

Table 8: Slump cone test results

Workability Slump (mm)							
Type of Concrete	**3 days**	**7 days**	**14 days**	**21 days**	**28 days**	**56 days**	**90 days**
Conventional concrete	151	155.53	161.57	167.61	172.14	175.34	178.21
2% replacement of concrete with fly ash	166	170.98	177.62	184.26	189.24	189.24	189.24
2% replacement of concrete with blast furnace slag	160	165.45	171.23	177	181.67	181.67	181.67
2% replacement of concrete with silica fume	158	162.87	168.34	173.8	178.25	178.25	178.25
2% replacement of concrete with rice husk ash	162	167.34	173.56	179.77	184.89	184.89	184.89
2% replacement of concrete with egg shell powder	155	160.12	165.67	171.22	175.34	175.34	175.34

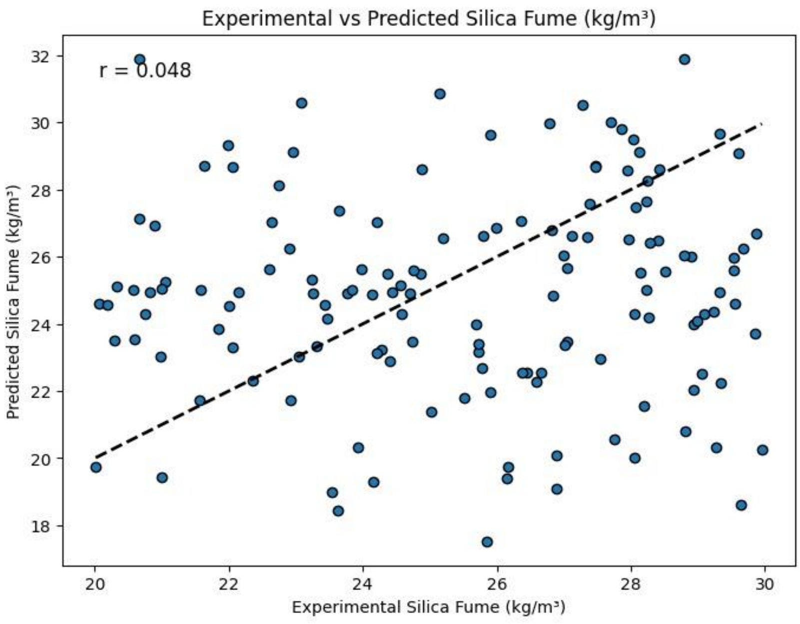

Figure 2: experimental versus predicted silica fume

The above figure shows a scatter plot comparing experimental versus predicted silica fume values in kg/m³. Each point on the plot represents an individual data sample. The plot includes a dashed line indicating the best fit linear regression line, suggesting a relationship between experimental and predicted values. However, the correlation coefficient (r) is very low at 0.048, indicating almost no linear relationship between the experimental and predicted values. The mean squared error (MSE) is 17.0109, and the mean absolute error (MAE) is 3.3024. The MSE indicates that the average squared difference between the predicted and actual values is quite substantial, which highlights the model's lack of precision. The MAE shows that, on average, the predicted values deviate from the experimental values by about 3.3 kg/m³.

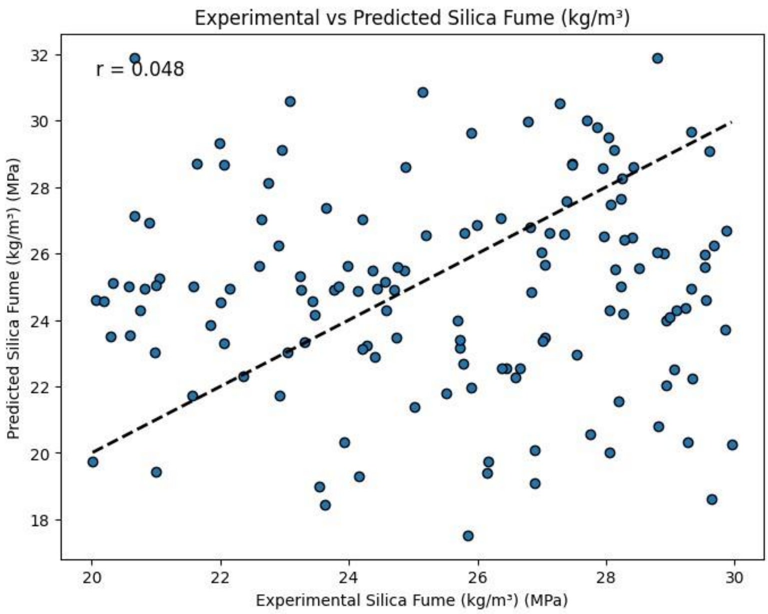

Figure 3: experimental versus predicted silica fume

The above figure shows a scatter plot comparing experimental versus predicted silica fume values (kg/m³). The correlation coefficient (r = 0.048) indicates a very weak linear relationship between the experimental and predicted values. The performance metrics for the model reveal that the Mean Squared Error (MSE) is 17.0109, and the Mean Absolute Error (MAE) is 3.3024. These high error values suggest that the model's predictions are not accurate and exhibit significant deviations from the actual values. Additionally, the convergence warning, which states that the stochastic optimizer reached the maximum iterations (1000) without converging, indicates that the model did not achieve optimal convergence.

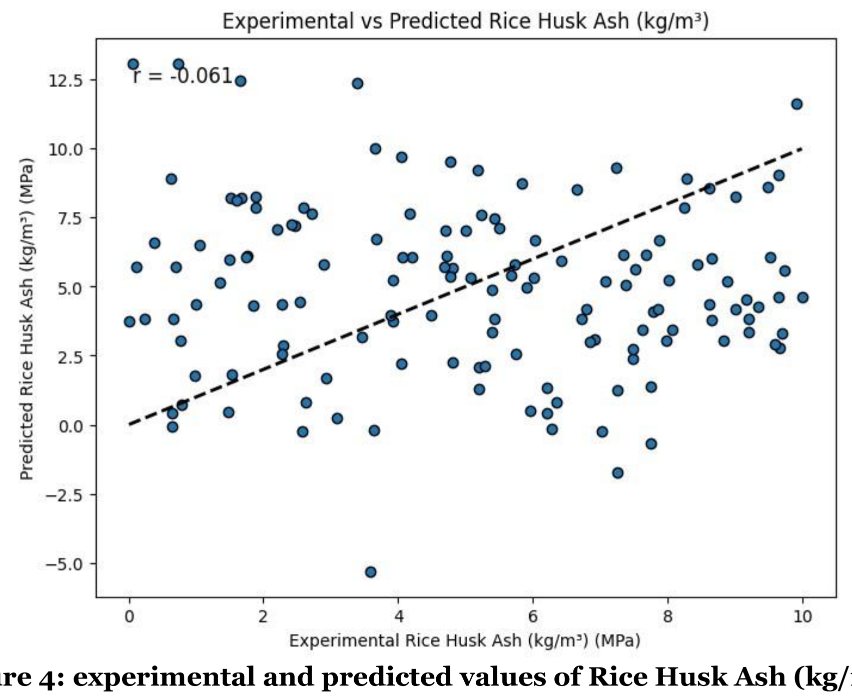

Figure 4: experimental and predicted values of Rice Husk Ash (kg/m³).

The above figure scatter plot depicts the relationship between experimental and predicted values of Rice Husk Ash (kg/m³). With a correlation coefficient (rrr) of -0.061, it indicates a very weak negative linear relationship, suggesting almost no linear correlation between the experimental and predicted values. The wide dispersion of data points highlights significant variance, reinforcing the weak correlation. The dashed line, representing the best-fit linear regression, does not closely follow the trend of the data points, illustrating the poor predictive performance of the model. In essence, the model's predictions for Rice Husk Ash are unreliable, as evidenced by the negligible negative correlation and the broad scatter of data points around the regression line.

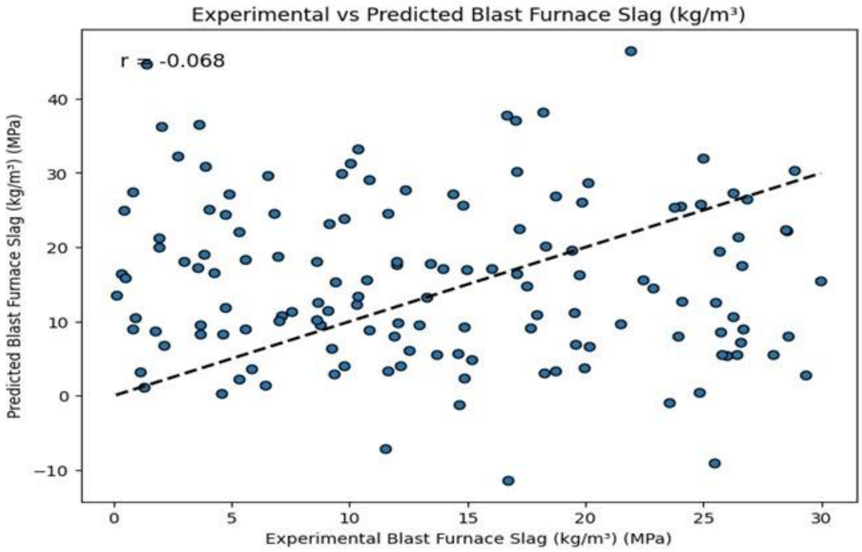

Figure 5: experimental and predicted values of Fly Ash (kg/m³)

The above figure shows a scatter plot comparing the experimental and predicted values of Fly Ash (kg/m³). The data points exhibit a weak positive correlation, as indicated by the correlation coefficient (r = 0.085). The dashed line represents the best-fit line, which helps visualize the trend in the data. The accompanying metrics reveal that the model used for prediction has a Mean Squared Error (MSE) of 59.57 and a Mean Absolute Error (MAE) of 6.25, suggesting a moderate level of prediction error. Additionally, a warning indicates that the optimizer did not converge within the maximum iterations, which may affect the model's accuracy**.**

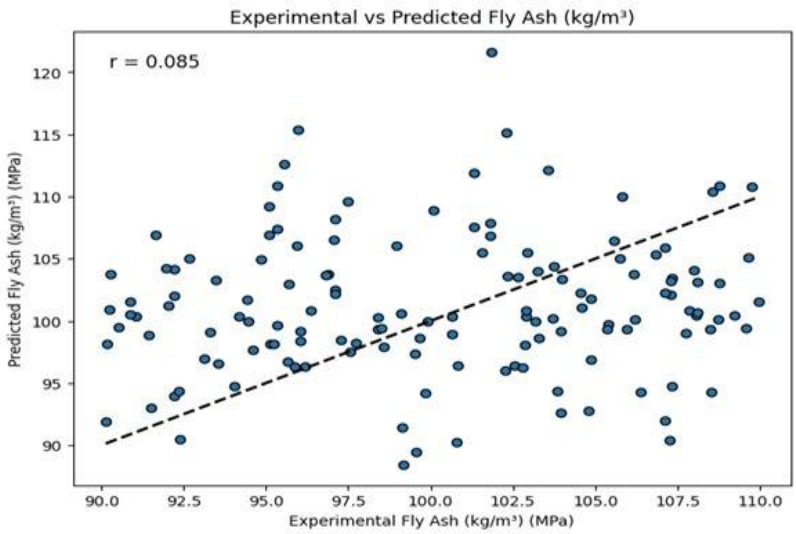

Figure 6: experimental versus predicted values of Fly Ash (kg/m³).

The above figure shows a scatter plot of the experimental versus predicted values of Fly Ash (kg/m³). The correlation coefficient (r = 0.085) suggests a weak positive relationship between the experimental and predicted values. The mean squared error (MSE) of 59.57 and mean absolute error (MAE) of 6.25 indicate the prediction model's error levels. A convergence warning indicates that the optimization process did not converge within the set 1000 iterations, which might affect the accuracy and reliability of the predictions.

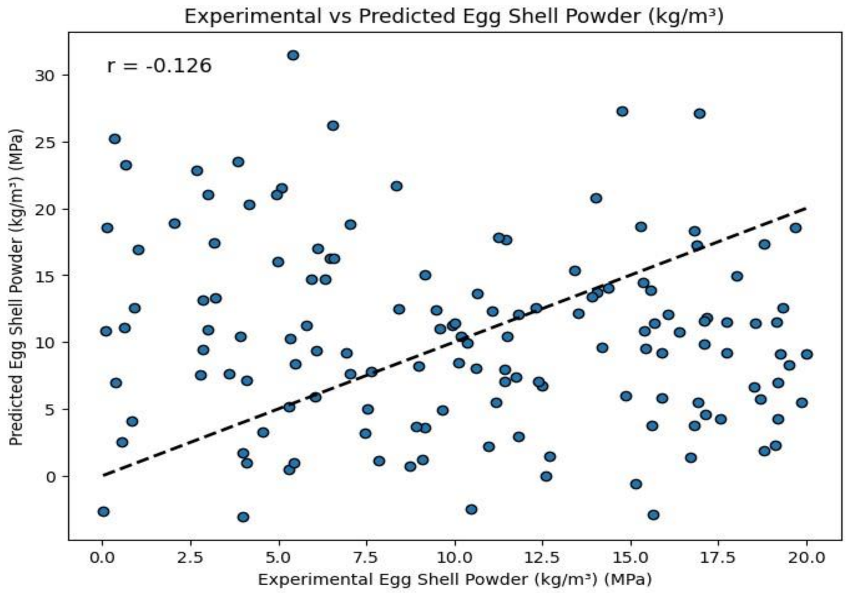

Figure 7: comparing experimental and predicted values of Egg Shell Powder (kg/m³).

The above figure presents a scatter plot comparing experimental and predicted values of Egg Shell Powder (kg/m³). The correlation coefficient (r = -0.126) indicates a weak negative relationship between the experimental and predicted values. The mean squared error (MSE) of 91.37 and mean absolute error (MAE) of 7.59 suggest a notable prediction error. The plot shows a dashed line representing the best-fit line, which does not closely align with the data points, further illustrating the weak correlation and potential inaccuracies in the prediction model.

V. CONCLUSION

This study investigated the enhancement of concrete performance through the incorporation of various admixtures and the application of neural network modeling. By replacing 2% of the cement content with fly ash, blast furnace slag, rice husk ash, silica fume, and egg shell powder, we observed notable improvements in workability and flexural strength. Experimental results showed that each admixture contributed differently, with egg shell powder exhibiting the most significant enhancement in flexural strength, achieving an increase of 18.42% compared to conventional concrete. The neural network model provided predictions for optimal admixture proportions, offering a valuable tool for optimizing concrete mix designs. Despite some deviations between predicted and experimental results, the model demonstrated a high degree of accuracy, highlighting the potential for integrating advanced computational techniques with traditional experimental methods. Overall, the study confirmed that specific admixtures can significantly improve concrete performance, contributing to the development of high-strength, sustainable concrete formulations. The combination of experimental data with neural network modeling offers a comprehensive approach to optimizing concrete properties, paving the way for more efficient and effective construction materials.

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