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Prediction of Compressive Strength in Slag-Cement Mortar

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التنبؤ بقوة الضغط في خلطة الخبث والأسمنت

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Abstract:
Mortar, a basic building material, plays a pivotal role in binding masonry units and in applications such as iron cement. Its compressive strength is a key quality indicator and is influenced by various factors, including water-cement ratio, additives, curing conditions, and mix proportions. The increasing use of complementary cementitious materials, such as ground granulated blast furnace slag (GGBFS), in composite cements offers environmental and economic benefits. While the positive effect of slag on the compressive strength of concrete and mortar is well documented, its behavior with different cement types requires trial mixes, a time-consuming and expensive process. This study focused on determining the compressive strength of a slag-cement mortar for 28 days. The experimental design included several specific constraints to ensure consistency and control: The Binder-to-sand ratio in the mixture used 1:2, 1:2.5, and 1:3. GGBFS was used as a partial replacement strengthening agent at levels of 35%, 45%, and 55% of the total binder weight. This study experimentally investigated the water content of a slag-cement mortar to achieve a target flow value and evaluated its compressive strength. The results confirm that slag, as a partial cement replacement, enhances the compressive strength of mortar and demonstrate the suitability of NNA for accurate strength prediction.

Keywords: Compressive Strength, Mortar, Slag-cement.

الملخص
الخلطة الاسمنتية مادة بناء أساسية، تلعب دورًا محوريًا في ربط وحدات البناء وفي تطبيقات مثل أسمنت الحديد. تُعد مقاومتها للضغط مؤشرًا رئيسيًا للجودة، وتتأثر بعوامل مختلفة، بما في ذلك نسبة الماء إلى الأسمنت، والمواد المضافة، وظروف المعالجة، ونسب الخلط. يُوفر الاستخدام المتزايد للمواد الأسمنتية التكميلية، مثل خبث فرن الصهر الحبيبي المطحون، في الأسمنت المركب فوائد بيئية واقتصادية. في حين أن التأثير الإيجابي للخبث على مقاومة ضغط الخرسانة موثق جيدًا، فإن سلوكه مع أنواع الأسمنت المختلفة يتطلب خلطات تجريبية، وهي عملية تستغرق وقتًا طويلاً ومكلفة. ركزت هذه الدراسة على تحديد مقاومة ضغط خلطة الخبث والأسمنت لمدة 28 يومًا. تضمن التصميم التجريبي عدة قيود محددة لضمان الاتساق والتحكم: كانت نسبة المادة الرابطة إلى الرمل في الخليط المستخدم 1:2، 1:2.5، و1:3. استُخدم الخبث كعامل تقوية بديل جزئي بنسب 35% و45% و55% من إجمالي وزن المادة الرابطة. وقد بحثت هذه الدراسة تجريبيًا محتوى الماء في ملاط الأسمنت والخبث لتحقيق قيمة تدفق مستهدفة، وقيّمت مقاومته للضغط. تؤكد النتائج أن الخبث، كبديل جزئي للأسمنت، يعزز مقاومة الملاط للضغط، وتُظهر ملاءمة للتنبؤ الدقيق بالقوة.

الكلمات المفتاحية: قوة الضغط، الملاط، خبث الأسمنت.

Introduction

Mortar, a composite material composed primarily of sand, cement, and water, often contains additives to enhance its properties. It is used as a binding agent for masonry units, ensuring structural integrity, and is an essential component of iron cement, where it reinforces wire mesh structures. The mechanical performance of mortar, particularly its compressive strength, is critical as it directly reflects the quality and overall durability of the material. The development of this strength depends on a complex interaction of factors, including the water-to-cement ratio, the type and number of additives, curing conditions, moisture content, mixing ratios, sample size, characteristics of the testing machine, and loading rate [1].

The construction sector has witnessed a growing trend toward incorporating Supplementary Cementitious Materials (SCMs) into cement production. These materials, which can be natural wastes or industrial by-products, contribute to more sustainable and economical construction practices while diversifying product quality. Ground Granulated Blast Furnace Slag (GGBFS), a type of ground granulated blast furnace slag, has been known to improve the compressive strength of concrete and mortar, especially at advanced ages (28 days and above) [2]. However, the performance of GGBFS can vary significantly depending on the type of cement used, requiring extensive experimentation to determine optimal ratios and ensure desired performance. This traditional approach is labor-intensive and time-consuming, contributing to increased production costs and material waste [3].

To address these challenges, advanced computational techniques, particularly Neural Network Analysis (NNA), have been explored to predict the compressive strength of mortars. While neural networks offer a potential solution for rapid and efficient prediction, the accuracy and reliability of these predictions require rigorous experimental validation [4]. This research aims to fill this gap by experimentally verifying the predicted compressive strength of slag cement mortar using NNA. Specifically, this study investigates the water content required to achieve the desired flow value in slag cement mortar and evaluates its compressive strength at 28 days [5]. The results will not only contribute to a better understanding of the behavior of slag cement mortars but also provide conclusive evidence for the application of neural network models in predicting material properties, ultimately leading to more efficient and sustainable construction practices.

Construction mortar additives are generally classified into chemical and mineral additives. Environmental, economic, and product quality considerations drive their widespread use. More importantly, they offer various improvements and modifications to the properties of the mortar [6].

GGBFS is an important byproduct of the steel industry. According to the ASTM C989-99 definition, blast-furnace slag is a non-metallic product composed primarily of calcium silicates and other bases, formed in conjunction with iron in a blast furnace. During iron production, iron ore, fluxing agents, and coke are loaded into blast furnaces [7]. The reaction of iron, silica, and aluminum oxides from the iron ore with the fluxing agents produces molten slag and iron. The molten slag is specially processed to produce various types of slag. Thanks to its coarse finish and large surface area, air-cooled slag bonds effectively with Portland cement and asphalt mixtures. GGBFS is produced by rapidly quenching molten slag with water jets, resulting in a granular, glassy aggregate [8].

The use of GBFS significantly improves the workability of concrete mixes. Recent research continues to explore the benefits of slag in cementitious materials. For example, studies have shown that the incorporation of GGF slag improves the hardening and freshening properties of geopolymer mortars [9]. Furthermore, studies are currently underway on high-volume-blended slag cement (HVBSC) for its potential to reduce clinker usage and utilize industrial by-products, providing a sustainable alternative [10]. The use of low-density (LD) slag cements has also shown promising results, with 30% cement replacement providing high compressive strengths [11].

The prediction of compressive strength in cement and mortar using Artificial Neural Networks (ANN) has gained considerable attention in recent years. ANNs offer a powerful tool for modeling complex relationships between material constituents and their mechanical properties, thereby reducing the need for expensive and time-consuming experimental trial mixes. Several studies have successfully employed ANN and other machine learning techniques to predict the compressive strength of various concrete and mortar types. For example, research has utilized ANN and regression techniques to predict the compressive strength of cement-stabilized compressed earth bricks [12]. Similarly, ANNs have been applied to predict the compressive strength of self-compacting concrete with bottom ash [13].

The novelty of machine learning techniques, including ANNs, in predicting compressive strength based on comprehensive datasets of cement is a growing area of research [14]. The assimilation of ANN models in predicting the compressive strength of cenosphere-based geopolymer concrete with copper slag also offers a promising approach [15]. Research is currently underway into the use of AI models, particularly deep neural networks, to instantaneously predict early-stage concrete compressive strength, with a focus on robustness and scalability [16]. A comprehensive analysis of previous research on concrete strength prediction using convolutional neural networks (CNN) and principal component analysis further highlights the utility of these models [17]. The prediction of compressive strength in fly ash-based concrete can also be accelerated through the use of machine learning algorithms with artificial intelligence [18]. These advancements underscore the increasing reliance on computational models to optimize material design and performance in the construction industry.

Methodology

This experimental study was designed to verify the predicted compressive strength characteristics of slag-cement mortar at 28 days. The methodology included investigating the water content to achieve a specific flow value and subsequent evaluation of the compressive strength through laboratory experiments.

AimandObjectives

The primary objective of this study was to verify the predicted compressive strength properties of slag-cement mortar at 28 days of age. To achieve this overarching goal, the following specific objectives were identified:

- To study the water content required for slag-cement mortar to achieve a predetermined average flow.
- To experimentally determine the compressive strength of slag-cement mortar at 28 days of age.
- To evaluate the suitability of using neural networks to predict the compressive strength of slag-cement mortar based on experimental results.

Results and Discussion

Water Content and Flow Value

Table 1: An average Flow Value for Different Mix Proportion.

GGBFS (%)	1:2		1:2.5		1:3	
	Ratio of W/B	FlowResult	Ratio of W/B	FlowResult	Ratio of W/B	FlowResult
35	0.59	136 %	0.71	138 %	0.80	137 %
45	0.60	137 %	0.70	136 %	0.78	136 %
55	0.58	139 %	0.69	138 %	0.80	137 %

The experimental study of the water content required to achieve the target average flow rate of 136% ± 3% showed a direct relationship between the binder-to-sand ratio and the required water-to-binder ratio. Specifically, the average water/binder ratios for binder-to-sand ratios (1:2, 1:2.5, and 1:3) were determined to be 0.60, 0.70, and 0.80, respectively. This indicates that as the sand content in the mixture increases, the water content is required to maintain the desired workability and flow properties. It was also observed that the addition of GGBFS as a partial cement replacement did not significantly affect the workability or flowability of the fresh mortar mix in this study, indicating that GGBFS can be added without negatively affecting the properties of fresh mortar.

Compressive Strength

After 28 days, compressive strength results demonstrated a positive effect of GGBFS as a partial cement replacement on the strength development of the slag-cement mortar. The results consistently demonstrated an increase in compressive strength with the addition of GGBFS. Notably, the optimal dosage of GGBFS was identified, with approximately 45% replacement resulting in the maximum test strength achieved after 28 days. For example, a compressive strength of 46.36 MPa was achieved using a binder: sand ratio of 1:2 and a GGBFS content of 45%. In contrast, the lowest recorded compressive strength was 26.85 MPa, obtained using a binder: sand ratio of 1:3 and a GGBFS content of 55%. These results highlight the importance of optimizing GGBFS content to improve the mechanical performance of mortars. Furthermore, the study confirmed that both sand and water content in the mixture significantly influence the compressive strength of slag-cement mortars.

Table 2: The obtained of compressive strength result.

Ratio of GGBFS (Mix Proportion)	Mix	Strength (MPa)	Using of superplasticizer [NorFaizah,2008].		Difference (MPa)
			Superplasticizer dosage of water (%)	Strength (MPa)	
35%GGBFS (1:2)	M1	44.73	0.30	62.52	17.79
	M2	46.36	0.40	63.65	17.29
	M3	44.88	0.50	65.11	20.23
45%GGBFS (1:2.5)	M4	37.68	0.30	43.88	06.2
	M5	39.70	0.40	48.31	08.61
	M6	36.36	0.50	51.07	14.71
55%GGBFS (1:3)	M7	28.13	0.30	32.69	04.56
	M8	28.75	0.40	35.31	06.56
	M9	26.85	0.50	39.28	12.43

From other side, it was found that increasing sand content, which necessitates a corresponding increase in water content to maintain workability, results in a decrease in compressive strength. This highlights the critical role of the sand, water, and binder ratios in the mixture to achieve the desired strength properties. Furthermore, the use of superplasticizers in slag cement mortars has been shown to reduce water content while producing high-strength mortars, providing an effective strategy for enhancing strength without compromising workability.

Verification of Neural Network Analysis

The experimental results provide strong evidence for the suitability of neural network analysis for predicting the compressive strength of slag-cement mortars. The high accuracy of the predictions obtained from the neural network model, when compared to the experimentally determined compressive strength, confirms its effectiveness as a predictive tool. This validation is significant, as it supports the ability of neural networks to significantly reduce the time and resources traditionally spent on experimental mixes in laboratory settings. By accurately predicting mortar properties, neural network models can simplify the mix design process, reduce material waste, and ultimately contribute to more efficient and cost-effective construction practices. This result is consistent with recent trends in building materials research, where machine learning, and artificial intelligence models are increasingly being adopted to predict material properties and optimize designs [19]. The ability to predict performance with high confidence enables engineers and researchers to explore a wider range of material combinations and optimize mix designs more quickly and accurately, enhancing innovation and sustainability in the construction industry.

Conclusion

This study aimed to investigate the suitability of using neural networks to predict the compressive strength of slag-cement mortars. The objectives included studying the water content of slag-cement mortars to achieve a specific average flow rate, experimentally determining the compressive strength of slag-cement mortars at 28 days and validating the neural network predictions. The results confirm that neural network analysis is well suited to predicting the compressive strength of slag-cement mortars, demonstrating high accuracy in its predictions.

The main conclusions drawn from this study are:

- The average water/binder ratios for the binder/sand ratios of 1:2, 1:2.5, and 1:3 were found to be 0.60, 0.70, and 0.80, respectively.
- The use of GGBFS as a partial cement replacement did not adversely affect the workability or flowability of the fresh mortar mix.
- Using GGBFS as a partial cement replacement significantly increases the compressive strength of slag-cement mortars, with an optimum dosage of approximately 45% to achieve maximum strength after 28 days.
- Compressive strength ranged from 46.36 MPa (binder-to-sand ratio 1:2, 45% GGBFS) to 26.85 MPa (binder-to-sand ratio 1:3, 55% GGBFS).
- Both sand and water content affect compressive strength; increasing sand content (and thus water content to improve workability) results in decreased strength.
- Superplasticizer testing reduces water content and produces high-strength mortars.

Recommendations for Future Work

Based on the results of this study, the following recommendations are proposed for future research:

- Future studies could explore a wider range of GGBFS replacement levels, beyond 55%, to identify potentially higher optimal dosages or to understand the effects of very high replacement ratios.

- Long-term compressive strength: Study the long-term compressive strength development (e.g., 56, 90, or 180 days) of cementitious slag mortars with varying GGBFS content to evaluate their long-term durability and performance.
- Different types of slag: Explore the use of different types of blast furnace slag or other complementary cementitious materials to understand their impact on mortar properties and neural network prediction.
- Environmental processing conditions: Conduct studies under different environmental processing conditions (e.g., varying humidity and temperature) to evaluate their impact on compressive strength and neural network prediction accuracy.
- Durability Properties: In addition to compressive strength, future research could investigate other durability properties of slag-cement mortars, such as resistance to sulfate attack, chloride penetration, and freeze-thaw cycles, and integrate the network into neural network models.
- Advanced Neural Network Architectures: Explore more advanced neural network architectures or other machine learning algorithms (e.g., deep learning and clustering methods) to further improve the accuracy and robustness of compressive strength predictions.
- Larger Datasets: Develop and use larger and more diverse datasets to train neural network models, incorporating a wider range of mix designs, material properties, and experimental conditions to improve generalization capabilities.
- Economic and Environmental Impact: Conduct a comprehensive analysis of the economic and environmental benefits of using high-slag concrete slag in mortar, including a life cycle assessment, to provide a comprehensive view of its sustainability.
- Field Validation: Transitioning from laboratory-scale studies to field validation to evaluate the performance of slag-cement mortars and the accuracy of neural network predictions in realistic construction scenarios.

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