PREDICTION OF COMPRESSIVE STRENGTH EFFECT OF CEMENT CONCRETE INCORPORATING FINE ELECTRIC ARC FURNACE SLAG AGGREGATES

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(Received: May 05, 2026; Revised: June 01, 2026; Accepted: June 11, 2026)

DOI: 10.31130/ud-jst.2026.24(6A).287E

Abstract - Fine electric arc furnace slag (EAFS) aggregates exhibited a positive effect on the compressive strength of steel slag concrete. This study analyzes the influence of replacing conventional fine aggregates with EAFS and develops predictive models to estimate the resulting enhancement in compressive strength. A regression model incorporating the compressive strength of the control concrete without EAFS and their contents as input variables achieved a coefficient of determination of $R^2 = 0.76$. To further improve predictive performance and ensure model reliability with the limited dataset (33 samples), an Artificial Neural Network (ANN) model was developed using 10-fold Cross-Validation. The optimized ANN model yielded a higher coefficient of determination $R^2 = 0.8487$ and a robust Root Mean Square Error (RMSE = 13.51%). These parameters confirm that the ANN model provides superior predictive accuracy compared to conventional regression. The models are applicable within the range of control compressive strength $f_{c0} = 21.5$–66.1MPa and slag replacement ratio $P_{cSlag} = 10\%$–100%.

Keywords - electric arc furnace slag (EAFS); steel slag concrete; compressive strength; ANN model

1. Introduction

The application of industrial by-products as construction materials has become increasingly imperative to mitigate the environmental impacts of waste disposal, reduce the exploitation of natural resources, promote a circular economy, and advance sustainable development in the construction sector [1]. Among these materials, steel slag aggregates (SSA) have been approved for use as embankment fill in accordance with TCVN 13906:2024 [2], and they may also partially replace aggregates in cement concrete or asphalt concrete [3], [4]. SSA can be employed as a replacement for coarse aggregates, fine aggregates, or both, and may also function as a supplementary cementitious material to enhance the mechanical and durability properties of concrete [5]. The impacts of SSA on compressive behavior have been comprehensively reviewed and analyzed in the literature [6]. In general, SSA can increase or decrease the compressive capacity of steel slag concrete (SSC), depending on SSA type, the aggregate replacement rate, and the strength of the control concrete incorporating SSA [5].

The enhancement in the compressive strength of SSA-modified cement concrete can be explained by the higher abrasion resistance and hardness of SSA compared with those of natural aggregates [7]. In addition, owing to its water absorption, SSA may act as an internal curing additive within the concrete matrix [8]. Furthermore, SSA may contain reactive components that, when appropriately activated in different concrete composites, promote the formation of additional hydration products [9]. Conversely, the heterogeneous composition, high porosity, and particularly the volumetric instability associated with the expansion of SSA upon contact with water may adversely affect the strength and durability of SSC [10]. Therefore, SSA should be properly treated or stored under controlled environmental conditions for a sufficient period to achieve volumetric stability. This stabilization process is typically facilitated by carbonation, which reduces the free CaO and MgO content in SSA [11].

Numerous review studies have investigated the application of SSA in cement concrete. Among them, Nguyen et al. [5] conducted a systematic review to comprehensively evaluate the factors influencing SSC compressive strength. The authors concluded that among various types of SSA, electric arc furnace slag (EAFS) has the greatest positive effect on compressive strength. SSA incorporation can maintain or even enhance the compressive strength of conventional concrete when used appropriately. Regarding particle size, fine SSA has been shown to perform more effectively than coarse SSA when used as an aggregate replacement in conventional concrete, especially EAFS, to improve compressive strength. Fine SSA contributes positively due to its water absorption capacity and its more uniform dispersion within the concrete matrix, which enhances internal curing efficiency compared with coarse SSA. Therefore, developing predictive models to quantify the effect of using SSA as a replacement for fine aggregates on the compressive strength of SSC is necessary and practically significant.

Currently, numerous approaches are available for predicting the compressive performance of cement concrete based on mixture composition. Such predictive methods help reduce the time and cost associated with experimental compressive-strength testing. However, traditional linear regression models are often unable to adequately capture the complex, nonlinear relationships between material constituents and compressive strength. Recently, artificial intelligence methods, especially artificial neural networks (ANNs), have been widely applied to predict concrete compressive strength [12]. To mitigate the risk of overfitting inherent in small datasets, a K-fold cross-validation approach was employed, as recommended in recent studies for material property prediction [13], [14]. This employment ensures that every data point is used for both training and validation, enhancing the generalization capability of proposed models. ANN models can handle nonlinear interactions among multiple input variables, such as the water-to-SSA ratio, SSA content, and control concrete strength, thereby providing more accurate predictions than conventional statistical approaches.

Therefore, investigating the application of ANN for predicting the compressive strength of cementitious concrete incorporating fine EAFS as a partial replacement for fine aggregates is necessary. The proposed model will be developed based on a dataset compiled from the previous study [5]. In addition, multivariate regression models will be established before implementing ANN. The findings are expected to provide a practical and reliable tool to support the mix design of SSC and to promote its broader application in sustainable construction.

2. Data collection and description methods

2.1. Data collection

According to Nguyen et al. [5], the use of EAFS as a replacement for fine aggregate in cement concrete yields greater compressive strength enhancement than other types of SSA and alternative replacement approaches. Therefore, this study specifically extracted and analyzed data from previous investigations that used EAFS to replace fine aggregate in cement concrete. Among the 570 data points compiled by Nguyen et al. [5], 33 correspond to cases involving EAFS as a fine aggregate substitution. The dataset includes the following input variables: compressive strength of control concrete without SSA, f_{c0} (MPa); water-to-cement ratio, W/C (%); cement content per cubic meter of concrete, Cement (kg); and fine aggregate replacement ratio by EAFS, $PcSlag$ (%). The output variable is the compressive strength effect, denoted as Effect (%), as calculated using Equation (1). These 33 data points were collected from previous studies ([15] - [23]) and are presented in Table 1.

$$\text{Effect} = \frac{(f_c - f_{c0})}{f_{c0}} \times 100\% \quad (1)$$

Where, Effect is the change in the compressive strength as incorporating SSA (%), and f_c, and f_{c0} are compressive strengths of SSC and the control concrete, respectively (MPa).

Descriptive statistics for the variables in Table 1 were computed using the R environment. The analysis reveals that the initial compressive strength, f_{c0} changes from 21.5 MPa to 66.1 MPa, with a mean of 33.8 MPa and a median of 32.3 MPa. The W/C ranges from 0.345 to 0.690, with a mean of 0.517 and a median of 0.514. The cement content per cubic meter of concrete (Cement) ranges from 300 kg to 500 kg, with a mean of 365 kg and a median of 350 kg; however, 15 data points are missing. The fine aggregate replacement ratio by SSA (P_{cSlag}) ranges from 10% to 100%, with a mean of 52% and a median of 50%. The compressive strength effect (Effect) of concrete incorporating SSA ranges from -24.7% to 78.7%, with a mean value of 24.6% and a median of 15.7%. These results demonstrate substantial potential for improving compressive strength when fine EAFS is used as a replacement for natural fine aggregates.

Table 1. *Dataset collected from previous studies ([15] - [23])*

No	f_{c0} (MPa)	W_C (%)	Cement (kg)	P_{cSlag} (%)	Effect (%)	Ref
1	39.1	0.5	350	30	15.1	[15]
2	46.4	0.5	350	30	11.6	[15]
3	39.1	0.5	350	50	12.3	[15]
4	46.4	0.5	350	50	0.9	[15]
5	66.1	0.3	500	50	4.1	[16]
6	66.1	0.3	500	100	-3.8	[16]
7	49.2	0.4	400	100	32.9	[17]
8	46.9	0.5	378	10	-13.8	[18]
9	46.9	0.5	378	20	-10.7	[18]
10	46.9	0.5	378	30	-21.9	[18]
11	32.3	0.4	350	25	-0.8	[19]
12	32.3	0.4	350	50	-24.7	[19]
13	22.3	0.5	-	20	13.1	[20]
14	21.8	0.6	-	20	15.7	[20]
15	21.5	0.6	-	20	14.9	[20]
16	22.3	0.5	-	40	32.8	[20]
17	21.8	0.6	-	40	32.2	[20]
18	21.5	0.6	-	40	29.9	[20]
19	22.3	0.5	-	60	46.6	[20]
20	21.5	0.6	-	60	50.7	[20]
21	21.8	0.6	-	60	51.0	[20]
22	21.8	0.6	-	80	66.7	[20]
23	22.3	0.5	-	80	66.6	[20]
24	21.5	0.6	-	80	66.4	[20]
25	21.8	0.6	-	100	78.7	[20]
26	22.3	0.5	-	100	77.5	[20]
27	21.5	0.6	-	100	74.7	[20]
28	51.0	0.6	350	100	3.9	[21]
29	34.3	0.5	320	10	3.0	[22]
30	34.3	0.5	320	15	11.0	[22]
31	34.3	0.5	320	20	16.7	[22]
32	34.3	0.5	320	25	24.4	[22]
33	40.8	0.7	300	100	34.8	[23]

2.2. Correlation analysis of variables

The correlation analysis of the independent variables influencing the compressive strength enhancement of cement concretes (Effect), conducted in R, is presented in Figure 1.

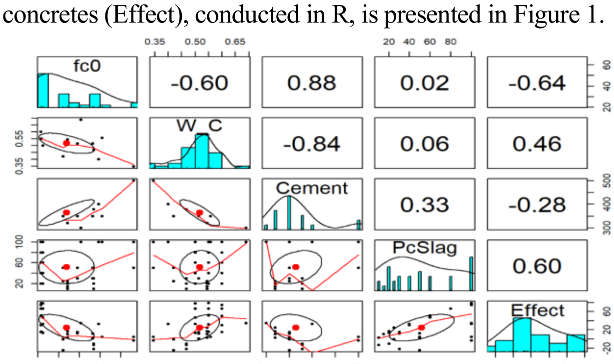

Figure 1. *Correlation analysis among variables*

Figure 1 indicates that the SSA replacement ratio (P_{cSlag}) is positively correlated with the compressive strength enhancement of cement concrete (Effect), with a correlation coefficient of r=0.60. In contrast, the correlation between the Effect and the initial compressive strength of the control concrete without EAFS (f_{c0}) is negative, with r=−0.64. This observation suggests that

EAFS replacement is more effective in concrete mixtures with lower control strength. The cement content (Cement) exhibits a strong positive correlation with f_{c0} (r=0.88). However, Cement shows only a weak negative correlation with the strength enhancement effect (Effect), with r=−0.28. The water-to-cement ratio (W/C) is negatively correlated with the control compressive strength, f_{c0} (r=−0.60), and positively correlated with the strength enhancement effect (Effect), with r=0.46.

The input variables f_{c0}, W/C, and P_{cSlag} exhibit relatively strong correlations with the output variable, Effect. Therefore, these three variables were selected as input parameters for the predictive model of compressive strength enhancement (Effect). Although the Cement variable was not directly included in the prediction model due to its relatively weak correlation with Effect, it demonstrates a strong positive correlation with f_{c0}. Consequently, incorporating f_{c0}, as an input variable, indirectly accounts for the influence of cement content in the predictive model for Effect.

3. Development of predictive models for the SSC compressive strength effect

3.1. Multivariate regression models

Based on the correlation analysis presented in Section 2.2, the input variables f_{c0}, W/C, and P_{cSlag} were selected, with Effect defined as the output variable. Using these three input variables, prediction model 1 was developed to estimate the compressive capacity enhancement of cement concrete. The formulation of Model 1 is presented in Equation (2), and the corresponding statistical analysis results are summarized in Table 2. Model 1:

$$Effect = b1 + b2 * f_{c0} + b3 * W\_C + b4 * P_{cSlag} \quad (2)$$

Table 2. *Statistical analysis results of the models*

Model	Coefficient	Estimate	SE	t value	Pr(>|t|)	Adjusted R^2	p-value
1	b1	28.05629	27.72278	1.012	0.320	0.7595	1.003e-09
	b2	-1.33698	0.23675	-5.647	4.21e-06		
	b3	24.42218	42.84063	0.570	0.573		
	b4	0.55957	0.08035	6.964	1.18e-07		
2	b1	43.19291	7.88065	5.481	5.99e-06	0.7649	1.408e-10
	b2	-1.41782	0.18744	-7.564	1.96e-08		
	b3	0.56378	0.07911	7.127	6.30e-08		

The predictive model indicates that the coefficient of determination (R^2) and the adjusted ones are relatively high, namely 0.782 and 0.7595. The variables f_{c0} and P_{cSlag} are statistically significant in the model (Pr < 0.001), whereas the W/C variable is not statistically significant (Pr = 0.573 > 0.05). Consequently, W/C was excluded from the model, and a revised multivariate regression model was developed using only two input variables: f_{c0} and P_{cSlag}.

The regression model for predicting compressive strength enhancement based on these two input variables is presented in Equation (3), and the corresponding statistical analysis results are summarized in Table 2. Model 2:

$$Effect = b1 + b2 * f_{c0} + b3 * P_{cSlag} \quad (3)$$

The regression Model 2 indicates that, despite using fewer input variables than Model 1, the coefficient of determination (R^2) and the adjusted one remains comparable, with values of 0.7796 and 0.7649, respectively. All model parameters are statistically significant (Pr < 0.001).

Based on the statistical analysis results in Table 2, the final multivariate regression equation (Model 2) for predicting the compressive strength effect is fully displayed in Equation (4).

$$Effect = 43.19291 - 1.41782 * f_{c0} + 0.56378 * P_{cSlag} \quad (4)$$

(a)
(b)
(c)
(d)

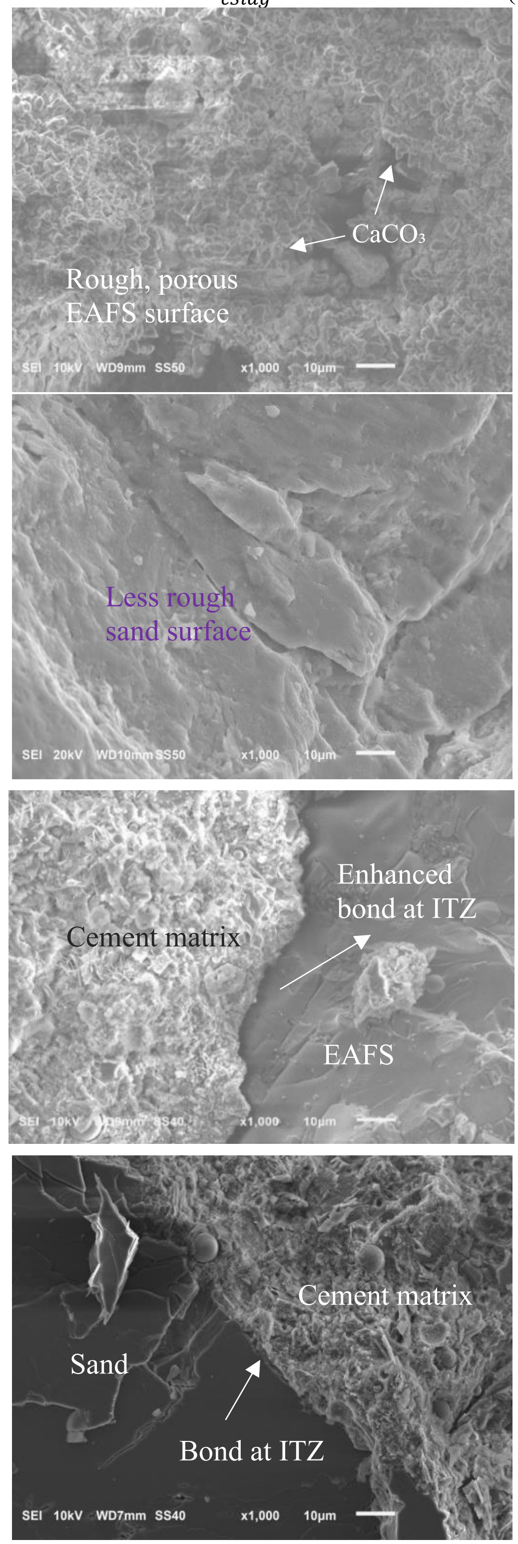

Figure 2. *Surface morphology of SSA (a) compared with natural sand (b); ITZ between cement matrix and SSA (c), and sand (d)*

It can be observed from Equation (4) that the compressive strength effect is inversely proportional to the control concrete strength. The relation exhibited a higher effect of f_{c0} than P_{cSlag} in the effect. This trend also suggests that replacing fine aggregate with EAFS is more effective at improving compressive strength in normal-strength concrete (typically with f_{c0} below 45 MPa). This finding is in agreement with previous studies. Furthermore, the compressive strength enhancement is directly proportional to the fine slag replacement ratio. This finding is further explained by observations from SEM-based microstructural analyses. The analyzed specimens were prepared under conditions in which both natural sand and fine EAFS were water-saturated before mixing. Note that the model samples (EAFS-cement matrix) were prepared with a water/cement ratio of 0.3 and coated with a thin platinum layer before observations using a JSM-6010 PLUS/LV microscope. As shown in Figures 2a and 2b, SSA exhibits a rougher, more porous surface texture than natural sand. At higher magnification, numerous $CaCO_3$ crystals can be observed, formed by carbonation reactions involving free CaO and $Ca(OH)_2$ when SSA is exposed to the natural environment. Consequently, when SSA is incorporated into cement concrete, good bonding is achieved at the fine SSA-cement matrix interfacial transition zone (ITZ) (Figure 2c), comparable to that observed with natural sand (Figure 2d). In addition, the cement matrix surrounding SSA exhibits greater hydration from internal curing, thereby contributing to the compressive strength of SSC.

3.2. ANN model

To simplify data collection for model inputs and facilitate comparison between predictive approaches, the artificial neural network (ANN) model was developed using the same two input variables (f_{c0} and P_{cSlag}) and one output variable (Effect) as employed in Model 2.

To address the challenge of a small dataset (n=33) and avoid the unreliability of a fixed data split, a 10-fold Cross-Validation technique was employed. This approach provides a more generalized assessment by using every data point for both training and testing across different folds.

To mitigate overfitting, the ANN architecture was optimized to a single hidden layer with 5 neurons, following the principle of parsimony. A weight decay of 0.1 was applied as a regularization measure. The cross-validation results showed an R^2 of 0.8487, an RMSE of 13.51%, and a Mean Absolute Error (MAE) of 10.33%. While these values are more conservative than those from more complex models, they provide a much more realistic and credible representation of SSC strength predictions.

The predictive performance of the optimized ANN model is visually assessed using a regression plot of experimental and predicted values, as shown in Figure 4a. The data points are closely distributed along the 45-degree dashed line (y = x), indicating strong agreement between the laboratory measurements and the model outputs. With a coefficient of determination (R^2 = 0.8487), the model demonstrates a robust ability to capture variations in compressive strength across a wide range of values. This level of accuracy, achieved through a simplified architecture and 10-fold cross-validation, confirms that the model is well-generalized and provides a significant improvement over traditional linear regression methods.

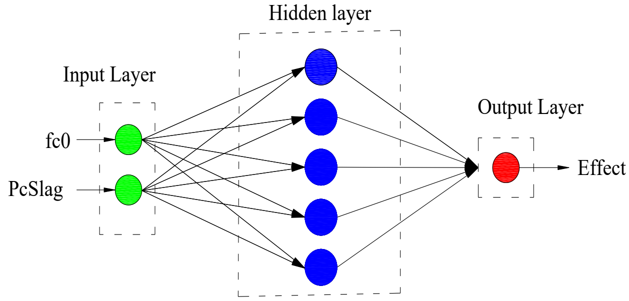

Figure 3. *ANN architecture to determine the compressive strength effect*

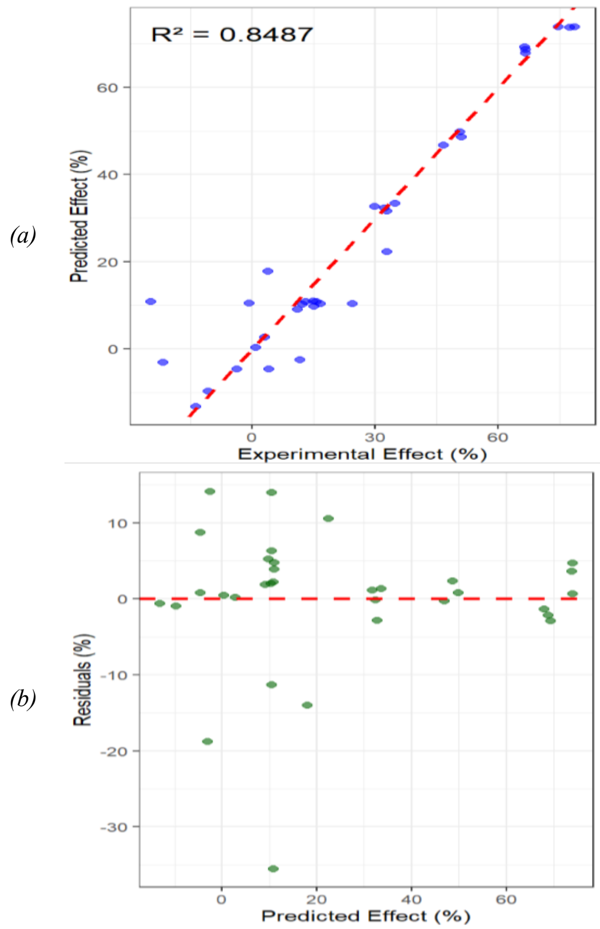

Figure 4. *Performance analysis of the optimized ANN model: (a) Predicted vs. Experimental values; (b) Residual plot*

To further verify the reliability of the proposed ANN model and assess potential overfitting, a residual analysis was conducted (Figure 4b). The residuals, representing the differences between experimental and predicted values, are randomly scattered around the zero-horizontal axis without any discernible systematic patterns or trends. This random distribution suggests that the model is an effective relationship between the input variables (f_{c0}, P_{cSlag}) and the strength effect rather than merely memorizing the noise in the 33-sample dataset. The absence of heteroscedasticity and no clear bias in the residual plot reinforce the statistical validity of the proposed ANN framework for predicting the performance of concrete incorporating fine EAFS aggregates.

4. Conclusion

This paper assessed the influence of fine EAFS and other relevant parameters on SSC compressive strength enhancement and developed predictive models to estimate the strength effect. The main findings can be reported as follows:

- Utilization of EAFS as a substitution for fine aggregate exhibited a positive correlation with compressive strength. This improvement is attributed to the enhanced interfacial transition zone, resulting from the rough surface texture of fine SSA and its internal curing effect, both of which promote hydration.

- A multivariate regression model (Equation 4) was developed to predict compressive strength enhancement, using control concrete (without SSA) strength and EAFS replacement ratio as input variables. The model achieved a coefficient of determination of $R^2 = 0.76$, providing a straightforward equation for practical estimation.

- The ANN model, validated through a 10-fold Cross-Validation procedure, demonstrated enhanced predictive capabilities ($R^2 = 0.85$) over the linear model. With a simplified architecture of 5 hidden neurons, the model proved to be promising and effective for predicting the compressive strength effect within the data range ($f_{c0} = 21.5$–66.1 MPa and $P_{cSlag} = 10\%$–100%). Future studies with larger datasets are recommended to improve the predictions.

Acknowledgments: This research is funded by Funds for Science and Technology Development of The University of Danang under project number B2023-DN02-18.

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