

# A Multiple Linear Regression Prediction of Concrete Compressive Strength Based on Physical Properties of Electric Arc Furnace Oxidizing Slag

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**Abstract:** Various physical properties in electric arc furnace (EAF) slag will result in different concrete physical characteristics. If concrete compressive strength could be predicted using physical properties in EAF slag, both cost and time could be saved and better compressive strength could also be achieved. The better compressive strength could also be achieved. Since there was no previous study in which the compressive strength was predicted, the multiple linear regression (MLR) method was employed to predict concrete compressive strength of EAF slag in this study. When constructing the model, the minimum mean absolute percentage error (MAPE) of 3.77 % and minimum mean square error (MSE) of 4.00 could be achieved using MLR. Using MLR, it is predicted that the minimum MAPE of 2.20 % and minimum MSE of 46.95 could be achieved. Therefore, MLR could be applied successfully in predicting compressive strength. The results also indicated that the compositions of slag could be applied on prediction of compressive strength well.

**Keywords:** Multiple linear regression; Concrete compressive strength; Physical properties; Electric arc furnace oxidizing slag.

## 1. Introduction

Electric arc furnace oxidizing slag (EAF slag) is a by-product produced from steel manufacturing processes. In melting processes, EAF slag is produced at proportion of 10-15 % of the manufacturer's steel productions. The annual production of EAF slag in Taiwan is estimated to be approximately one million tons. Through suitable processes such as crushing and sieving, EAF slag can be treated as a resource and applications are found in cement industry, ready-mix concrete, roadway base and subbase, and agricultural soil improve-

ment. Survey data from Germany and Japan indicate that the amounts of recycled slag had reached 85% [1]. As supplies of natural aggregates are dwindling in Taiwan, the use of slag as a substitute for natural aggregate is becoming an important issue. EAF slag was deposited in landfill in the past due to the poor quality of the EAF and instable material compositions. With recent plant upgrades and improved operation processes, the quality of slag has significantly improved and become stable. Therefore, through appropriate proc-

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esses including magnetic screening, crushing, and sieving, EAF slag is proposed to be used as coarse aggregate in making concrete [2].

Various physical properties of EAF slag including dry-nodded unit weight (DNUW), Los Angeles abrasion test (LAAT), saturated surface-dry (SSD) specific gravity (SSDSG), loss of sodium sulphate soundness test (LSSST), and rate of absorptive (RA) will result in different concrete compressive strength. If concrete compressive strength could be predicted using physical properties of EAF slag, cost and time could be saved. A better compressive strength could also be achieved. In the past, grey system theory and artificial neural network have been used on the prediction of solid waste properties [3-5]. To gain consistent results from the investigation data and predict the concrete compressive strength, the multiple linear regression method (MLR) was evaluated as a suitable method.

MLR is one of the most widely used methods for expressing the dependence between a dependent variable and several independent variables. If the relation between the concrete compressive strength and physical properties of EAF slag could be found using MLR, a better control strategy could be sought. However, there is no study in which MLR is adopted for predicting compressive strength. This paper shows the originality or novel methodology.

Since the predicting performance of MLR is good, so the objectives of this study are using MLR to establish the relationship between the concrete compressive strength and physical properties of EAF slag, then to predict the concrete compressive strength.

$$[\text{concrete compressive strength}] = a_1 \times [\text{DNUW}] + a_2 \times [\text{LAAT}] + a_3 \times [\text{SSDSG}] + a_4 \times [\text{LSSST}] + a_5 \times [\text{RA}] + \text{Constant} \quad (1)$$

Eq. (1) described how the average response of concrete compressive strength changed with the independent variables, i.e. DNUW, LAAT, SSDSG, LSSST, and RA.

For the least-squares model, the best-fitting

## 2. Materials and methods

### 2.1. EAF slag

Sixty slags samples were collected from various steel manufacturing plants of electric arc furnace considering geographical distribution, these slags were obtained from steel plants located in northern, central, and southern Taiwan, respectively. Then these 60 slags were analyzed for their physical properties including DNUW, LAAT, SSDSG, LSSST, and RA. The analytical methods included ASTM (American Society for Testing and Materials) C114, C25-36 and C311. Subsequently, a commercial ASTM Type I Portland cement (PC) was used to form concrete with the replacement of natural aggregate using these EAF slags. The EAF slags were used to replace natural aggregate, at replacement levels of 100%. The mix design procedures outlined in ACI (American Concrete Institute) 211.1 were used to produce concrete specimens. The Chinese Nation Standard 1232 was adopted for testing the compressive strength.

### 2.2. Brief description on MLR

MLR determines the relationship between two or more independent variables and a dependent variable by fitting a linear equation to observed data. Every value of the independent variable is associated with a value of the dependent variable. For example, the regression equation for five independent variables including DNUW, LAAT, SSDSG, LSSST, and RA is defined as follows:

equation for the observed concrete compressive strength data was calculated by minimizing the sum of the squares of the vertical deviations from each data point to the regression equation (if a data point lay on the fitted line

exactly, then its vertical deviation was 0). The least-squares estimates  $a_1$  to  $a_5$  and constant were computed by MATLAB software. When constructing MLR, 5 (MLR5-1), 4 (MLR4-1), 3 (MLR3-1), and 2 (MLR2-1) physical properties of EAF slag with higher correlation coefficient (R) were taken as the input variables, respectively. The MLR constructed in this study represented the relationship between compressive strength and physical properties with different R. In MLR, the physical properties served as the input variables.

### 2.4. Error analysis

In order to evaluate the prediction accuracy of MLR, the mean absolute percentage error (MAPE) was employed and described

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{obs_i - pre_i}{obs_i} \right| \times 100\% \quad (6)$$

where MAPE is MAPE,  $obs_i$  is the investigation value,  $pre_i$  is the prediction value.

In addition, mean square error (MSE) was also employed and described

$$MSE = \frac{1}{n} \sum_{i=1}^n (obs_i - pre_i)^2 \quad (7)$$

### 3.1. Variation of physical properties

The 60 slags were analyzed for their physical properties including DNUW, LAAT, SSDSG, LSSST, and RA, and the results are summarized in Figure 1. Among the total numbers of data, the numbers for constructing and testing (predicting) were 50 and 10, respectively.

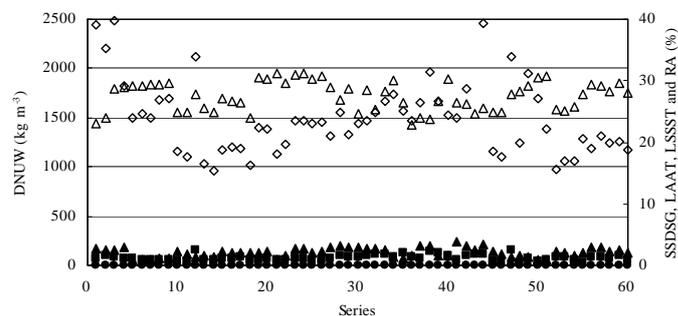


Figure 1. Variation of physical properties including DNUW, LAAT, SSDSG, LSSST, and RA.

### 3.2. R of physical properties

The R values between the compressive strength and different physical properties including DNUW, LAAT, SSDSG, LSSST, and RA were 0.39, 0.08, 0.33, -0.22, and -0.16, respectively. The absolute values of R were in the order: DNUW > SSDSG > LSSST > RA > LAAT.

According to the results, the selected input variables in four types of MLR were shown in Table 1.

Table 1. The selected input variables in MLR

MLR	Input variables
MLR5-1	DNUW, SSDSG, LSSST, RA, LAAT
MLR4-1	DNUW, SSDSG, LSSST, RA
MLR3-1	DNUW, SSDSG, LSSST
MLR2-1	DNUW, SSDSG

### 3.3. Simulation of compressive strength

When constructing MLR5-1, the regression equation for five physical properties including DNUW, LAAT, SSDSG, LSSST, and RA was defined as follows:

$$[CCS] = 0.018641823 \times [DNUW] + 0.604797486 \times [LAAT] + 9.180348233 \times [SSDSG] - 9.658145664 \times [LSSST] - 0.640228076 \times [RA] + 177.5444042 \quad (2)$$

When constructing MLR4-1, the regression equation for four physical properties including DNUW, SSDSG, LSSST, and RA was defined as follows:

$$[CCS] = 0.018790771 \times [DNUW] + 10.51819163 \times [SSDSG] - 5.179214169 \times [LSSST] - 0.06798196 \times [RA] + 181.5598781 \quad (3)$$

When constructing MLR3-1, the regression equation for four physical properties including DNUW, SSDSG, and LSSST was defined as follows:

$$[CCS] = 0.018879138 \times [DNUW] + 10.53162112 \times [SSDSG] - 5.197810128 \times [LSSST] + 181.2481505 \quad (4)$$

When constructing MLR2-1, the regression equation for four physical properties including DNUW, SSDSG, and LSSST was defined as follows:

$$[CCS] = 0.02496547 \times [DNUW] + 7.674785297 \times [SSDSG] + 172.9578115 \quad (5)$$

where CCS is the abbreviation symbol of concrete compressive strength. Because the predicting error should be reduced as low as possible, the significant figures in Eq. (2) – (5) and Table 2 were chosen. Additionally, the coefficients in Table 2 showed a positive or negative effect of different physical properties

on the compressive strength. After constructing MLR models, the MAPE and MSE values between observed values and simulation values were calculated to evaluate the performance of different MLR models. All the MAPE and MSE values are shown in Table 3.

Table 2. The coefficients in MLR

MLR	DNUW	SSDSG	LSSST	RA	LAAT	Constant
MLR5-1	0.018641823	9.180348233	-	-	0.604797486	177.5444042
			9.658145664	0.640228076		
MLR4-1	0.018790771	10.518191630	-	-	-	181.5598781
			5.179214169	0.067981960		
MLR3-1	0.018879138	10.531621120	-5.197810128	-	-	181.2481505
MLR2-1	0.024965470	7.674785297	-	-	-	172.9578115

Table 3. MAPE and MSE between the predicted and investigated values using different MLR

	Construction of model		Prediction of model	
	MAPE	MSE	MAPE	MSE
MLR5-1	3.77	118.23	3.30	75.88
MLR4-1	3.98	127.50	2.20	47.03
MLR3-1	3.98	127.50	2.20	46.95
MLR2-1	4.00	132.96	2.52	51.20

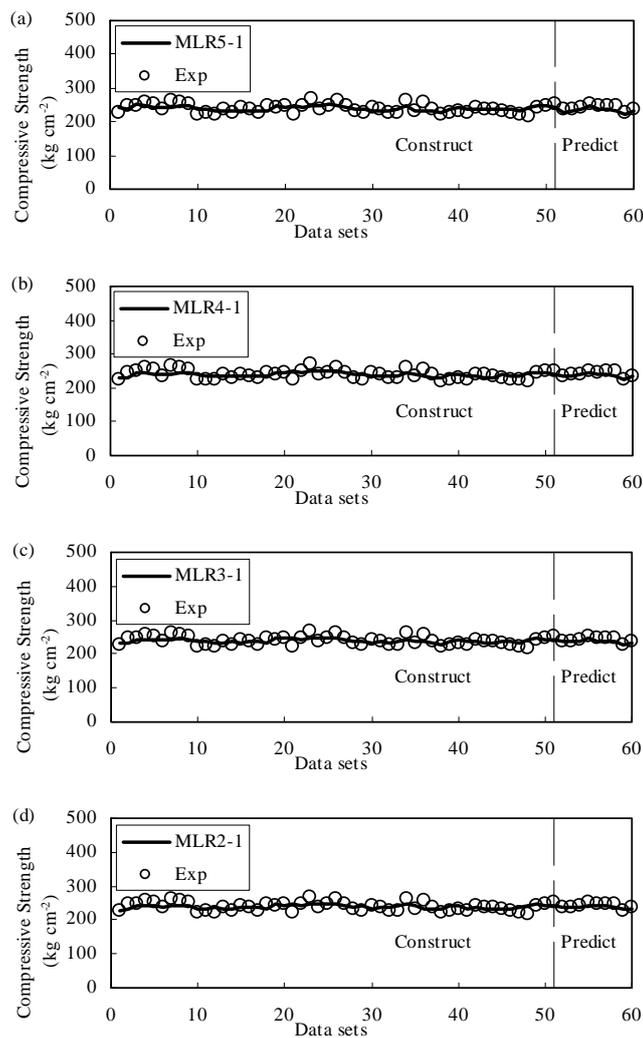


Figure 2. Prediction results of compressive strength using different MLR. (a) MLR5-1, (b) MLR4-1, (c) MLR3-1, (d) MLR2-1. The hollow dots in the figure denoted the experimental data, the solid line denoted the simulated values. The vertical line represented the boundary between constructing data and predicting data.

Figure 2 (a) – (d) depicts the prediction results using MLR5-1, MLR4-1, MLR3-1, and MLR2-1, respectively. The MAPE values for MLR construction lay between 3.77 % and 4.00 %, and the MSE values for MLR construction lay between 118.23 and 132.96. When predicting, the MAPE values lay between 2.20 % and 3.30 %, respectively. Their MSE values fell in the range of 46.95 to 75.88.

According to Table 3, the prediction performance of MLR5- 1 was the best when constructing model. But the performance of MLR3-1 was the best when predicting the concrete compressive strength. The possible reason was that the deviation of data set was different.

In this study, when constructing model, the minimum values of MAPE and MSE were 3.77 % and 118.23, respectively. When predicting, the minimum MAPE and MSE were 2.20 % and 46.95, respectively. Therefore, MLR could be applied successfully in predicting compressive strength. In addition, a good fitness could also be achieved using MLR in which the physical properties were adopted as the input variables. After prediction, it is suggested that the constructed MLR can be used in the objective function or constrains in linear program or other optimization for best adjusting physical properties in the future study.

#### 4. Conclusions

Four types of MLR were used to predict the compressive strength of EAF slag using physical properties as input variables in Taiwan. The results can be drawn as follows.

- The MLR in which the physical properties of electric arc furnace oxidizing slag served as the input variables excelled in predicting the compressive strength based on limited data because of low MAPE and MSE either

for model construction or for model prediction.

- Therefore, MLR could be applied in successfully predicting compressive strength when the information was not sufficient.
- The results also indicated that the physical properties of EAF slag could be applied on prediction of compressive strength well.

#### References

- [ 1] Motz, H., and Geiseker, J, 2001. Products of steel slags an opportunity to save natural resources, *Waste Manag.*, 21: 285.
- [ 2] Shi, C. 2002. Characteristics and cementitious properties of ladle slag fines from steel production, *Cement and Concrete Research* 32: 459.
- [ 3] Pai, T.Y., Chen, H.M., Chang, T.C., Chen W.F. and Ouyang C.F. 2006. Using ANN to predict the softening, melting and pouring points of sewage sludge ash during formation of slag. *Proceeding of IWA Specialized Conference on Sustainable sludge management: state of the art, challenges and perspectives*, May 29-31, Moscow, Russia: 373-377.
- [ 4] Pai, T.Y., Lin K.L., Shie, J.L., Chang, T.C. and Chen, B.Y. 2010. Predicting the co-melting temperatures of municipal solid waste incinerator fly ash and sewage sludge ash using grey model and neural network. *Waste Management & Research*. (In press)
- [ 5] Chen, L. 2010. Grey and neural network prediction of concrete compressive strength using physical properties of electric arc furnace oxidizing. *Journal of Environmental Engineering and Management*. (In press)