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ARTIFICIAL NEURAL NETWORK (ANN) MODELLING OF CONCRETE MIXED WITH WASTE CERAMIC TILES AND FLY ASH

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ABSTRACT: Waste generation has been the result of a growing demand in the construction industry. Thus, waste utilization has been one of the considerations in the construction industry towards sustainability. In the Philippines setting, many types of research were conducted to support the claim that wastes such as fly ash and waste ceramics have properties that are comparable to cement and aggregates. The American Concrete Institute standards were referred in the mix design of the specimens. This study incorporated the use of fly ash in the replacement of Type 1 Portland Cement and the substitution of waste ceramic tiles in replacing gravel as the coarse aggregates. Moreover, specimens were also subjected to varying days of curing to assess their strength development. Machine learning, namely Artificial Neural Network (ANN), was considered since there was an available wide range of data. This study aimed to provide an Artificial Neural Network (ANN) algorithm that will serve as a model to predict the compressive strength of concrete while incorporating waste ceramic tiles as a replacement to coarse aggregates while varying the amount of fly ash as a partial substitute to cement. The Artificial Neural Network (ANN) model used was validated to ensure the predictions are acceptable.

Keywords: Compressive strength, waste utilization, fly ash, ceramics, artificial neural network

1. INTRODUCTION

In Asia, 6.37 Billion ceramics were manufactured in the year 2010 and are used in the construction industry. Similarly, these ceramic tiles also produced most of the construction and demolition wastes worldwide, and these materials are only disposed of in the landfills [1]. Moreover, fly ash as another waste by-product has been massively produced in the countries that rely on coal-based electricity generation, such as the Philippines. These wastes generated have been the result of a growing demand in the construction industry. Thus, waste utilization has been one of the considerations in the construction industry towards sustainability. In the Philippines setting, many types of research were conducted to support the claim that these wastes have properties are comparable to cement and aggregates [2-8].

Many numerical modeling techniques have been introduced in the current technological era, and due to the availability of a wide range of data gathered during the experiment, machine learning model is considered, and one of them is Artificial Neural Network (ANN). Artificial Neural Network can handle nonlinear relationships between variables and incomplete data sets. Neural networks are very sophisticated modeling and prediction making techniques capable of modeling extremely complex functions and data relationships. The proposed Artificial Neural Network Model will be validated by involving an Output-Target plot as a guideline that provides insight into the measured variables and as a critical part of the analysis [6].

Thus, this study aimed to provide an Artificial Neural Network (ANN) model to predict the compressive strength of concrete incorporating waste ceramic tiles as a replacement to coarse aggregates while varying the amount of fly ash as a partial substitute to cement.

2. METHODOLOGY

The American Concrete Institute standards were referred in the mix design of the specimens.

This study incorporated the use of fly ash in the replacement of Type 1 Portland Cement, considering five replacements: 0%, 12.5%, 25%, 37.5% and 50%. Furthermore, the substitution of waste ceramic tiles in replacing gravel as the coarse aggregates were also considered with the following substitutions: 0%, 18.25%, 37.5%, 56.25% and 75% [9, 13-15]. Both waste materials replace in terms of mass percentage, moreover, a control mix was also considered which had pure cement and gravel. All of the replacements were the output of a rigorous Design of Experiments (DOE), thus, producing a total of 17 mixes.

Furthermore, these mix designs were given

Mix IDs in order to have a systematized way of labeling the specimens. "F" was used for Fly Ash, and "C" was used for waste ceramic tiles. The percentage replacement to either cement or gravel was represented by the number that immediately follows the acronym. For example, the Mix ID "F25C37.5" refers to the mix with 25% fly ash, 75% Type 1 Portland Cement, 37.5% waste ceramic tiles and 62.5% gravel. The complete list of Mix IDs is shown in Table 1.

Table 1. Mix IDs of the specimen used

Mix No.	Mix ID	Fly Ash Content	Ceramic Tiles Content
M1	F0 C0	0.00%	0.00%
M2	F50 C0	50.00%	0.00%
M3	F50 C 37.5	50.00%	37.50%
M4	F25 C37.5	25.00%	37.50%
M5	F37.5 C 18.75	37.50%	18.75%
M6	F25 C0	25.00%	0.00%
M7	F25 C 18.75	25.00%	18.75%
M8	F12.5 C 37.5	12.50%	37.50%
M9	F37.5 C37.5	37.50%	37.50%
M10	F0 C37.5	0.00%	37.50%
M11	F37.5 C56.25	37.50%	56.25%
M12	F12.5 C 18.75	12.50%	18.75%
M13	F25 C56.25	25.00%	56.25%
M14	F12.5 C56.25	12.50%	56.25%
M15	F50 C75	50.00%	75.00%
M16	F0 C75	0.00%	75.00%
M17	F25 C75	25.00%	75.00%

Before the mix was prepared, the raw materials were subjected to rigorous tests following the American Society for Testing and Materials (ASTM), such as moisture content, specific gravity, and absorption tests [9-10], and unit weight and voids [11]. These results of tests are shown in Table 2.

Table 2. Summary of material properties

Description	Results
The dry rodded density of gravel	1567.839 kg/m^3
Specific Gravity of Cement	3.150
Specific Gravity of gravel	2.812
Specific Gravity of sand	2.505
Moisture Content of gravel	0.349%
Moisture Content of sand	1.566%
Absorption of gravel	1.639%
Absorption of sand	2.765%
Fineness modulus of Sand	2.760

It was derived by having a target nominal compressive strength of 28 MPa, which is typically used in the industry. A total of 306 specimens were prepared to accommodate the curing at 3 ages: 7, 28 and 56 days. The estimated mixing water that should be used is 184 kilogram per cubic meter of concrete, which considers a 25-100 mm slump and a maximum size of 19.0 mm of the aggregates. The water-cement ratio that was considered in this study upon further interpolation is 0.478.

Moreover, compressive tests were performed after the specified day of curing to determine the physical properties of the specimens. The load was applied to the specimen, and the maximum load that the specimen could carry was recorded. With this, the compressive strength was computed by simply dividing the maximum compressive load that the specimen was able to carry by its average cross-sectional area.

Once the data are available, Artificial Neural Network (ANN) commenced. Each ANN model consists of a data case having a set of input variables labeled by a set of output variables, the research ANN model classification of is shown in Figure 1.

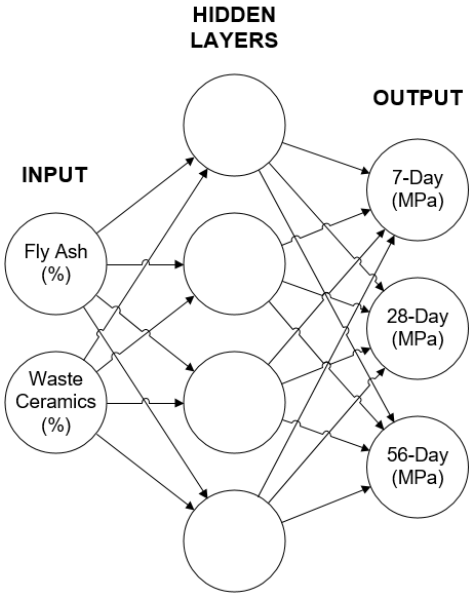

Figure 1. ANN model

The input and output variables are continuous. In the study the input and output variables are shown in Table 3:

Table 3. Input and Output Variables

Input Variable(s)	Output Variable(s)
1. 7-Days Compressive Strength 2. 28-Days Compressive Strength 3. 56-Days Compressive Strength	1. Fly Ash % 2. Ceramics %

The Artificial Neural Network (ANN) used was validated to ensure the predictions are

acceptable.

3. RESULTS & DISCUSSION

3.1 Compressive Strength

Compressive strength tests followed the standard methods stipulated under ASTM C 39 to ensure the results garnered are correct. The conventional mix attained its target nominal strength (28-Day) with 28.302 MPa. The early and late compressive strengths of the conventional mix at 7 and 56 days of curing periods were 21.645 MPa and 28.722 MPa, respectively. Among all modified mixes, F50C0 and F25C75 resulted to the least and highest compressive strengths at all ages with 26.343-MPa and 38.112-MPa nominal strengths, respectively. The complete compressive strengths of all mixes are shown in Table 4:

Table 4. Compressive strengths of all mixes

MIX No.	MIX ID	Compressive Strengths (MPa)		
		7-day	28-day	56-day
M1	F0 C0	21.65	28.30	28.72
M2	F50 C0	19.07	26.34	28.41
M3	F50 C 37.5	21.68	27.85	33.88
M4	F25 C37.5	27.29	37.21	39.20
M5	F37.5 C 18.75	24.97	32.14	35.44
M6	F25 C0	25.51	33.88	38.09
M7	F25 C 18.75	27.78	34.51	38.95
M8	F12.5 C 37.5	30.96	37.44	41.57
M9	F37.5 C37.5	25.07	33.83	35.97
M10	F0 C37.5	29.00	32.14	38.00
M11	F37.5 C56.25	27.46	34.49	38.32
M12	F12.5 C 18.75	26.00	34.06	37.90
M13	F25 C56.25	25.15	34.17	38.28
M14	F12.5 C56.25	27.53	27.23	36.36
M15	F50 C75	24.53	33.21	41.78
M16	F0 C75	24.86	33.95	39.66
M17	F25 C75	32.06	38.11	44.70
Minimum		**19.07**	**26.34**	**28.41**
Maximum		**32.06**	**38.11**	**44.70**

Compressive strength tests were conducted at three curing periods: 7 days, 28 days and 56 days. A sample plot is shown in Figure 2. This was done in order to have a representation of the compressive strengths of all mixes at early, nominal and late stages for further analysis. The results are shown in Figure 3.

All mixes had an increasing nominal compressive strength when waste ceramic tiles replacement was also increased except for the mix with 12.5% fly ash replacement, where the strength decreased from 37.5% to 56.25% waste ceramic tiles substitution.

In terms of cement variation, all combinations showed an increasing nominal strength up to an optimum amount. Based from the experimental data, all combinations have shown an optimum amount of 20% to 30% fly ash replacement except for the mix with 37.5% waste ceramic tiles replacement, which had an optimum amount of 10% to 20% fly ash substitution. Moreover, all combinations with 50% fly ash substitution attained less compressive strengths relative to mixes with 0% fly ash replacement.

Based on the Student's T-test conducted with 95% significance level, the compressive strengths of F50C0, F50C37.5 and F12.5C56.25 were found out to be statistically similar to the conventional mix at the 28th day-period. These mixes had 2-MPa decrease in strength than the conventional mix.

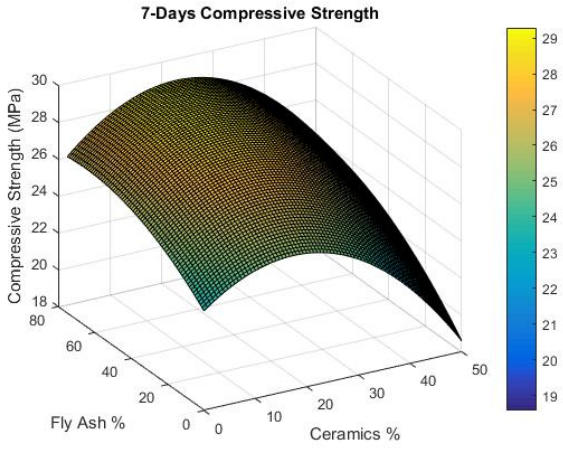

Figure 2. 7-Days Compressive Strength (Early)

The pozzolanic reaction has played a major role in the strength development of the modified mixes considering that both waste materials used, ceramic tiles and fly ash, possessed pozzolanic properties as inferred from the related literature. Aside from F50C0, all compressive strengths at the 56-day period exceeded the strength of the conventional mix. On the other hand, F0C37.5 and F12.5C56.25 produced compressive strengths less than F0C0 at the 28-day period. In terms of the modified mixes, 30% to 70% increase in strength was observed from the 7 to 56-day span.

With regards to the bonding of the aggregates, the particles of the cement paste of all mixes were fibrillating from 7 to 56 days of curing periods. This allowed the cement paste to better bond with the other aggregates. However, when fly ash was introduced into the mix, the particles of cement paste became more spherical –as the percentage of

fly ash replacement was increased, more spherical particles were also observed. These spherical particles could have caused a weaker bonding among the aggregates thus providing weaker strength.

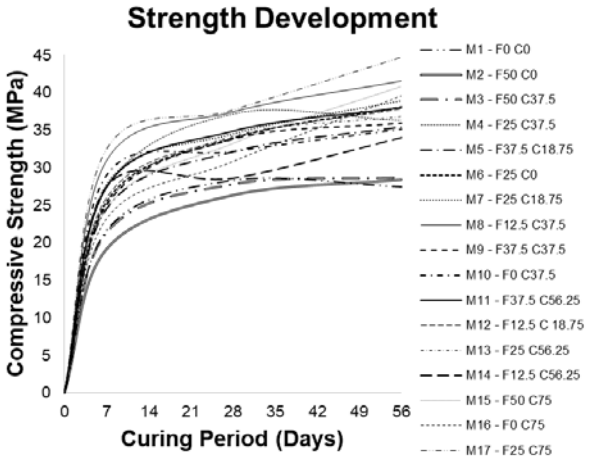

Figure 3. Strength development of the mixtures

Optimization results have indicated that the optimum combination of fly ash and waste ceramic tiles replacements at the 28th day-period was 25% fly ash and 75% waste ceramic tiles with 0.92 desirabilities to attain the maximum compressive strength of 37.188 MPa.

3.2 *Artificial Neural Network Model*

Neural networks have a remarkable ability to derive and extract meaning, rules, and trends from complicated, noisy, and imprecise data. They can be used to extract patterns and detect trends that are governed by complicated mathematical functions that are too difficult, if not impossible, to model using analytic or parametric techniques. One of the abilities of neural networks is to accurately predict data that were not part of the training dataset, a process known as generalization. Given these characteristics and their broad applicability, neural networks are suitable for applications of real-world problems [16].

The data garnered were divided into three (3) groups: 70% for training the neural network, 15% for validation and 15% for testing, shown in Table 5:

Table 5. Considerations in the Artificial Neural Network Model

Description	Value
Train Size	70%
Testing Size	15%
Validation Size	15%
Seed	1000

Multilayer Perceptron Networks (MLP) activation functions were considered for both hidden (input-hidden) and output (hidden-output) units. The activation functions for the hidden and output neurons used are the following, shown in Table 6.

By determining the number of neurons in the input and output layers, a number of hidden layers and the number of neurons in each hidden layer, the best Artificial Neural Network model for the mixtures can be garnered. The Multilayer Perceptron Networks (MLP) considered minimum hidden units of three (3) and maximum hidden units of thirteen (13).

Table 6. Activation functions for the hidden and output neurons [17]

Neuron Function	Description
Identity	The activation level is passed on directly as the output of the neurons
Logistic	This is an S-shaped (sigmoid) curve, with output in the range (0,1).
Tanh	The hyperbolic tangent function (tanh) is asymmetric S-shaped (sigmoid) function, whose output lies in the range (-1, +1).
Exp	Uses the negative exponential activation function

After numerous trial, the ANN structure 2-12-3 (2 input, 12-nodes and 3 output) with Tanh-Exponential Activation Functions was determined to be the best model to estimate early, nominal and late compressive strengths of the mixtures. The summary of the network performances is shown in Figure 4.

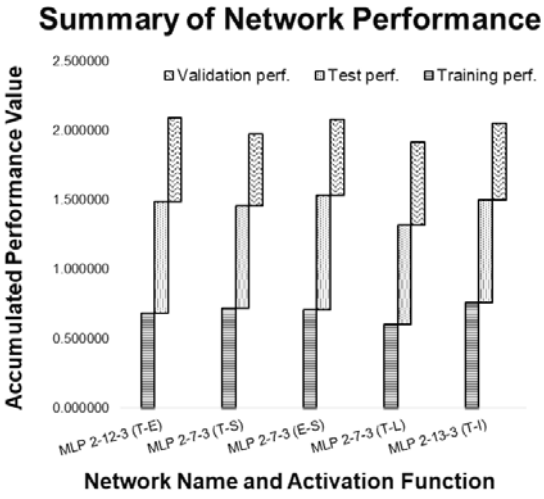

Figure 4. Summary of Network Performance

The model was able to give acceptable values of performance: 0.685130796, 0.801285056, and 0.606756221 for training, testing and validation, respectively.

To validate, the Target Compressive Strength vs. Predicted Compressive Strength Artificial Neural Network model were compared. A line that shows equality between the variable observed (Experimental Data) on the horizontal axis of a diagram and the variable predicted (Artificial Neural Network model) on the vertical axis. The plots should be near the equality line to ensure the predictions are acceptable, a sample Equality Line for the 7-Day Compressive Strength is shown in Figure 5.

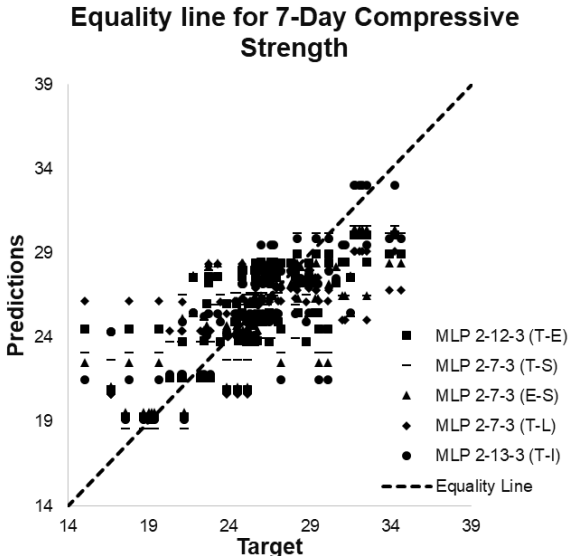

Figure 5. Equality line of the Artificial Neural Network model

4. CONCLUSIONS & RECOMMENDATIONS

Compressive strength tests followed the standard methods stipulated under ASTM C 39 to ensure the results garnered are correct. The conventional mix attained its target nominal strength (28-Day) with 28.302 MPa. The early and late compressive strengths of the conventional mix at 7 and 56 days of curing periods were 21.645 MPa and 28.722 MPa, respectively. Among all modified mixes, F50C0 and F25C75 resulted to the least and highest compressive strengths at all ages with 26.343-MPa and 38.112-MPa nominal strengths, respectively.

All combinations showed an increasing nominal strength up to an optimum amount. Based from the experimental data, all combinations have shown an optimum amount of 20% to 30% fly ash replacement except for the mix with 37.5% waste ceramic tiles replacement, which had an optimum amount of 10% to 20% fly ash substitution. Moreover, all combinations with 50% fly ash substitution attained less compressive strengths relative to mixes with 0% fly ash replacement.

The pozzolanic reaction has played a major role in the strength development of the modified mixes considering that both waste materials used, ceramic tiles and fly ash, possessed pozzolanic properties as inferred from the related literature.

The Artificial Neural Network provided a model that can predict based on extracted patterns and detected trends. The Target Compressive Strength vs. Predicated Compressive Strength by the Artificial Neural Network model was compared, and their plots are near the equality line, thus, acceptable.

To further improve the conduct of the study, it is recommended to provide superplasticizers or other additives in the mixes in order to address the high absorption rate of ceramic tiles that lead to poor workability. It is also recommended to provide other machine learning models.

5. ACKNOWLEDGMENT

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