Journal of Engineering Science and Technology
Vol. 19, No. 3 (2024) 744 - 761

ENHANCING COMPRESSIVE STRENGTH IN CONCRETE WITH WASTE CERAMIC TILES: EFFECTS OF SELECTED AGGREGATE MODIFICATION TREATMENTS, WATER-CEMENT RATIO AND CURING PERIODS FOR DECISION TREE REGRESSION ANALYSIS

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Abstract

Due to the ceramic tile waste's (CTW) negative impact on workability, this study incorporated three aggregate modification treatments (AMTs) on the CTWs, namely cement impregnation (CI), sodium silicate soaking (SS), and slurry wrapping (SW). Concrete batches were prepared, with varying CTW replacements of 0%, 25%, and 50% to gravel, and water-cement ratios (w/c) of 0.5 and 0.6. Slump tests and compressive strength tests at curing periods of 7 and 28 day were conducted. Experimental results showed that concrete mixes with CI treatment produced the highest compressive strength, while the concrete batches with 0.6 w/c produced higher compressive strengths. However, concrete mix that considered SW treatment showed a reduction in compressive strength relative to the mix with untreated CTW. The optimum design mix incorporated CI treatment, 25% CTW replacement, and 0.5 w/c. This mix yielded about 16.7% stronger nominal strength compared to the control mix. A decision tree regression (DTR) model was generated to predict the compressive strength based on different combinations for the concrete mix. Based on the model, the AMT showed the most influence on the prediction of compressive strength. Overall results indicate the use of CTW in sustainable concrete production could be further enhanced by CI treatment method.

Keywords: Aggregate treatment methods, Concrete compressive strength Machine learning, Sustainable concrete, Water-cement ratio.

1. Introduction

Global construction sectors strive for technological and methodological breakthroughs; however, these developments negatively impact the environment due to carbon dioxide emissions, and waste generation from the construction, restoration, and demolition of structures [1, 2]. As population and demand grows, the rate of concrete use increased about 10 billion tons per year. Billion tons of each material: water, cement, and aggregates, are needed to produce large amounts of concrete. This simultaneously decreases the already scarce natural resources and causes adverse effects on the environment; natural aggregate extraction can lead to erosions of coastlines and river deltas [3]. These situations amplify the need of sustainable or recycled materials.

Besides concrete, ceramic tile waste (CTW) is also a common construction and demolition waste produced [3-9]. Other studies suggested around 30% of raw ceramic materials are wasted in the ceramic tiles, contributing to land, air, and ground pollution [8]. There is also no indication that the waste ceramic materials would be recycled [4, 8].

To address the CTW issues, numerous studies proposed and investigated using CTWs as an alternative material for concrete production and the feasibility of its mechanical properties [3-9]. While these studies generally showed CTW can be an alternative to the conventional aggregates of concrete, it has been reported that the amount of required water essentially increases when these are incorporated into the concrete mix. This is highly associated with the high-water absorption capacity of ceramic tiles, resulting in poor workability of fresh concrete [5-7]. To address the poor workability, various studies have developed and evaluated treatment methods to improve waste aggregate properties.

This study examined the effect of partially combining untreated and treated CTW aggregates in concrete production. Gravel, the conventional coarse aggregate of concrete, was partially replaced with CTW at 0%, 25% and 50% substitutions. Considering the high absorption capacity of CTW aggregates, this study also considered aggregate modification treatment (AMT) methods based on previously established procedures, namely cement impregnation (CI) [10], sodium silicate soaking (SS) [11, 12], and slurry wrapping (SW) [13]. Furthermore, the water-cement ratio (W/C) of the concrete mix was varied, with 0.5 and 0.6 W/C. After 7 and 28 days of curing periods, all concrete samples were tested.

In this paper, AMTs are referred to as different methods involving concrete aggregate manipulation, using specific solutions to adjust their characteristics and performance [14, 15]. In this study, only CI, SS and SW treatments were analysed and compared. The CI treatment is a method that involves soaking concrete aggregates in a mixture of cement and water, possibly with the addition of admixtures such as superplasticizers [10]. The SS is a method that involves the soaking and submerging of concrete aggregates in a water and sodium silicate solution to reduce the absorption characteristics of the aggregate [11, 12]. And lastly, the SW treatment is a method that uses a mixture of different constituents like fly ash and minerals to improve the bond strength of concrete aggregates [13].

The research aims to determine whether partial amounts of treated CWTs can be an alternative for coarse aggregates in concrete. Different AMTs were compared and analysed as well as which is the optimum concrete mix combination.

After obtaining the experimental results, a decision tree regression (DTR) model was developed to predict the resulting compressive strength of the concrete mix, based on the parameters in this study: (1) AMT method, (2) CTW replacement, (3) w/c, and (4) curing period. Decision trees learn from inputting the data and results, to create a predictive model [16]. While there are several machine learning techniques involving decision tree models, such as Classification and Regression Tree (CART) [17], C4.5 algorithm [18], and Interactive Dichotomic 3 algorithm [19], CART was used to predict the concrete compressive strength, considering the 4 parameters investigated in this study. This is because CART can train multiple factors, interactions, and relationships, including both categorical and numerical data [20]. CART is also straightforward, which allows users to efficiently interpret and understand the generated data [21]. Additionally, the DTR model can identify which factors significantly impact the concrete mix, and the combination of the parameters.

2. Research Methodology

2.1. Experimental setup

This study's experimental design examines the qualities of aggregates, and of both fresh and hardened concrete. This was performed through preparing cylindrical concrete samples (100 mm x 200 mm), containing either treated or untreated CTW aggregates. The CTW coarse aggregate percent replacements were 0%, 25% and 50%, based on the findings of related literatures where CTW coarse aggregates were incorporated in the concrete mix [5-7], while the water-cement ratios (W/C) were limited to 0.5 and 0.6. Furthermore, based on similar research, the AMT methods employed in this study were the optimal application of slurry wrapping (SW), cement impregnation (CI), and sodium silicate coating (SS) [10-13], considering the treatment settings that have yielded the greatest outcomes for enhancing waste aggregates. These treatment procedures were used to CTW aggregates to improve their qualities as well as the properties of waste concrete, as outlined in Table 1.

Table 1. Mix and label summaries and tabulation.

AMT	W/C	CTW replacement	Specimen ID
Control	0.5	0%	CTRL W0.5
	0.6		CTRL W0.6
Untreated	0.5	25%	UNTR W0.5 C25
	0.6		UNTR W0.6 C25
	0.5	50%	UNTR W0.5 C50
	0.6		UNTR W0.6 C50
Slurry Wrapping	0.5	25%	SW W0.5 C25
	0.6		SW W0.6 C25
	0.5	50%	SW W0.5 C50
	0.6		SW W0.6 C50
Sodium Silicate Soaking	0.5	25%	SS W0.5 C25
	0.6		SS W0.6 C25
	0.5	50%	SS W0.5 C50
	0.6		SS W0.6 C50
Cement Impregnation	0.5	25%	CI W0.5 C25
	0.6		CI W0.6 C25
	0.5	50%	CI W0.5 C50
	0.6		CI W0.6 C50

Considering the parameters and their combinations, 18 mixes were made, with 6 concrete samples prepared for each mix. Among the 6 samples, 3 were tested after the 7-day curing period, while the other 3 specimens were tested after the 28-day curing period. The results obtained from the 3 samples represent the compressive strength of each mix at each curing day. A control mix was also produced among the 18 mixes, which only contained the conventional aggregates of concrete, to serve as baseline reference for the performance of the modified mixes, with both untreated and treated CTW coarse aggregates.

Using the applicable ASTM standards, the absorption, specific gravity of aggregates, workability, and compressive strength of concrete were determined in this study. The water-cement ratio and coarse particles of the concrete mixture were modified, in conjunction with incorporating various AMT techniques. Gravel, which is the typical coarse aggregate of concrete, was substituted with CTW, and the w/c was also altered.

All concrete samples were evaluated using ASTM C127, ASTM C143, and ASTM C39 to establish their absorption rate, workability, and compressive strength, respectively. To evaluate the correlations between CTW replacement and slump, and CTW absorption and slump, graphical analyses were conducted. Furthermore, the strengths of control, untreated, and treated batches were compared. These analyses were conducted to evaluate the efficacy of AMT methods in enhancing aggregate and concrete qualities to conform to concrete production standards.

2.2. Materials preparation

CTW was manually crushed using a hammer to reach the same nominal size as the natural aggregates utilized in the control setup. Figure 1 shows the aggregates that have been prepared for the experiment.

Fig. 1. Illustrative sample of crushed CTW aggregate used in this study.

On the other hand, the physical properties of the CTW produced were obtained by using applicable ASTM standards. Table 2 shows the results of the tests.

Table 2. Physical properties of raw CTW.

Property	Value
Specific Gravity (Dry)	1.83
Specific Gravity (SSD)	2.10
Absorption, %	14.62

2.3. Concrete mix design

The mix design of the specimens was determined using the absolute volume approach according to ACI 211.1. This procedure entailed utilizing the quantities displaced by the concrete mixture's components, namely water, cement, and coarse and fine aggregates. Table 3 displays the mix design of all specimens included in this study.

Table 3. Mix design of CTW mixtures.

Water-Cement (w/c) Ratio	0.5		0.6	
CTW % Replacement	25%	50%	25%	50%
Water, kg	2.00		2.00	
Cement, kg	4.00		3.33	
Coarse Aggregate, kg	4.50	3.05	5.30	3.50
Crushed CTW, kg	1.05	2.10	1.25	2.50
Fine Aggregate, kg	4.60	4.60	5.60	5.60

This study employed 3 treatment strategies: slurry wrapping (SW), cement impregnation (CI), and sodium silicate soaking (SS). The proportioning of mixtures is shown on Table 4.

Typically, SW treatment consists of a mixture of cement, water, and a pozzolanic substance. In this study, the pozzolanic material used was fly ash. After preparing the mixture shown in Table 4, the CTW aggregates were soaked for approximately 1 hour and aired-dried for 1 hour [13].

CI was conducted by soaking dry CTW aggregates in a solution of 10 L of water, and one (1) kg of cement for 24 hours. The soaked aggregates were then allowed to dry for 1 hour before being added to the concrete mixtures [10].

For the SS treatment, a soaking solution was prepared, containing 8% sodium silicate (Na_2SiO_3) mixed with water. Then, the CTW aggregates were submerged in the solution for 1 hour, before being removed for an additional 1 hour of natural drying [11, 12].

Table 4. Aggregate modification treatment (AMT) parameters.

AMT	Cement (kg)	Fly Ash (kg)	Water (L)	Na_2SiO_3 (mL)	Soaking Time (hour)	Drying Time (hour)
CI	1	0	10	0	24	1
SW	10	1.5	10	0	1	1
SS	0	0	10	800	1	1

All modified aggregates were placed into concrete compositions after drying time. Below is a table including the parameters for each treatment procedure.

After obtaining all the necessary aggregates, including the treated CTW aggregates, the concrete samples were prepared using the standards of ASTM C31M, followed by the conduct of slump test per concrete batch using a slump cone, in accordance with ASTM C143.

Moreover, to determine the concrete samples' compressive strength, ASTM C39M was utilized. The maximum load at which the concrete specimen failed was recorded using a universal testing machine.

2.4. Decision tree regression

Decision tree regression (DTR) models have been established as a machine learning tool for various applications in the field of science, medicine, and engineering, among others [22, 23]. As a technique for machine learning, the decision tree generates an appropriate classification and regression model for data. The categorization of a decision tree can be seen as an "if-then" technique. This has 3 components, namely: (1) selection feature, (2) building the decision tree, and (3) pruning the decision tree [24].

Figure 2 shows a schematic representation of a typical decision tree. The technique is configured similar to a tree, such that there is a set of branches that determine which decision to make. In particular, Classification and Regression Tree (CART) models adapt the biological understanding of trees, where the growth of the system originates from the roots that ultimately develop to a well-structured branches and leaves. The outcome is essentially based on the trends and patterns of the input data, which in this case, refer to the independent variables [25].

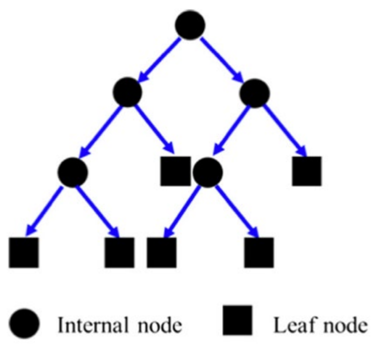

Fig. 2. Typical schematic diagram of a decision tree [22].

Each branch in a CART is called a “node”, and each CART model always has one “root node”. Referring to Fig. 2, the top-most node is defined as the CART model’s root node, while the one-way arrows that connect the nodes are called “branches”. Each branch will extend to a new node, and depending on the prediction algorithm, a “leaf node” is formed when such node does not split into branches any longer. The leaf node also defines the predicted value, based on the parameters and considerations above it. On the other hand, the nodes that still constitute branches are called “decision nodes”, which are also referred to as “internal nodes” in some cases. The decision nodes are the system’s independent variables that have a lower degree of importance compared to the root node. Generally, the decision tree's classification technique can be summarized as follows: initially, the decision tree determines the root node's characteristics depending on the learning method; then, the root node's data is branched into two or more sub-nodes that are either a leaf node or a decision node, each representing a category. This procedure concludes when all sub-nodes have become leaf nodes [24, 25].

In generating CART models, several algorithms have been developed to represent the model's estimation criteria in accurately identifying the order of the independent variables in the tree model. The estimation criteria consequently define which independent variable among the system constitutes a root node, and which variables would follow, depending on the measured impurity present in a given dataset. In R-based language, there are three commonly used estimation criteria, namely variance, Gini index, and entropy of information. Both Gini index, and entropy of information are typically used when the manner of prediction is categorical [25]. In this study, variance calculation was used, considering that the dependent variable of is the resulting compressive strength of the concrete mix, based on (1) AMT method, (2) CTW replacement, (3) w/c, and (4) curing period.

Although CART models may be generated manually using the established statistical approaches, there are widely available programming tools to aid researchers in generating such a model, including MATLAB [26], and Python [27]. In this study, Python was used in generating the CART model.

As part of data processing, decision tree pruning was performed to determine the most appropriate CART model. This study considered 8 different CART models with varying number of leaves, ranging from 2 to 9, and the resulting coefficient of determination, R^2, and root mean square error, RMSE, were tabulated for each model. Both R^2 and RMSE are commonly used in measuring the statistical difference between 2 variables; in this study, the variables were the predicted and actual test results. The best CART model was determined using the R^2 and RMSE values of all models. Equations (1) and (2) were used in calculating R^2 and RSME, respectively [28, 29].

$$R^2 = 1 - \frac{\sum_i (\hat{y_i} - y_i)^2}{(\bar{y} - y_i)^2} \tag{1}$$

where: R^2 = coefficient of determination, y = actual value, y^= predicted value, and y¯= statistical mean of the actual values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y_i} - y_i)^2}{n}} \tag{2}$$

where: RSME = root mean square error and n = number of data points.

Furthermore, after identifying the best CART model, Pearson's correlation was used to determine the acceptability of the model. Pearson's correlation requires the corresponding coefficient of correlation (R) of the chosen model to determine the relationship between the predicted values and actual values. Additionally, the range of R-values is -1 to 1, with positive values signifying a positive correlation, while negative ones show a negative correlation. An R-value equal to -1 or 1 indicates a perfect correlation between the variables; as such, an R-value close to -1 or 1 is desired [30].

3. Results and Discussions

3.1. CTW aggregates absorption

The absorption of the coarse aggregates of both treated and untreated samples was measured. Table 5 shows the results of the changes in absorption rates, following the different AMT methods used. As indicated in the table, aggregates treated with SW resulted in the highest reduction in absorption relative to the untreated aggregates, with 52.571% decrease. On the other hand, the aggregates that underwent CI treatment resulted in the least reduction, with only 11.322% decrease. These results were further analysed in conjunction with the slump test results.

Table 5. Absorption rates for each AMT method.

AMT Method	Absorption (%)	Decrease relative to Untreated (%)
Untreated	14.618	-
CI	12.963	11.322
SW	6.997	52.571
SS	10.811	26.043

3.2. Slump test results

Concrete workability is an important quality control measure of fresh concrete, as it relates to the ease of mixing, placing, and compacting of fresh concrete into the desired form while maintaining the target performance, and homogeneity [31]. Concrete workability is measured through conducting a slump test on fresh concrete, and the target slump is pre-determined during the preparation of the concrete mix design.

After conducting the slump test on each concrete mix, all batches achieved a slump value within the desired range of 80 mm to 100 mm. Although changes were anticipated due to the modification of w/c, and increase in CTW replacement, similar studies share the same observations, where equivalent values for workability were achieved using waste and standard concrete aggregates [32]. Nonetheless, the SS approach yielded the most workable mixes. This is a result of covering the coarse aggregates with sodium silicate, as opposed to cement and water mixtures utilized in SW and CI methods. The SS treatment resulted in aggregates with smoother surfaces, which might reduce the friction between concrete components.

Figure 3 shows the slump results vis-à-vis the corresponding CTW replacement values. As demonstrated by the graph, the presumption that increasing the CTW replacement would reduce the workability of concrete was invalidated. This was seen when the replacement percentage of SS W0.6 C50, SW W0.6 C25, and UNTR W0.6 C25 mixtures was increased from 25% to 50%. This is closely related to the size and surface roughness of the gravel employed in comparison to CTW aggregates.

A similar study has also identified that adopting larger aggregates can boost workability [33]. Even though the waste aggregates in this investigation were of a lower size, the presumption in the study that the slump would increase as the absorption rate decreased was again invalidated. This may suggest that the absorption of CTW aggregate within a mixture does not alter workability in a predictable manner for this range of replacement. Although having a 26.04% drop in absorption compared to the CI and SW procedures, the SS-treated CTW aggregates generated concrete mixtures with the largest slump. This is presented in Fig. 4.

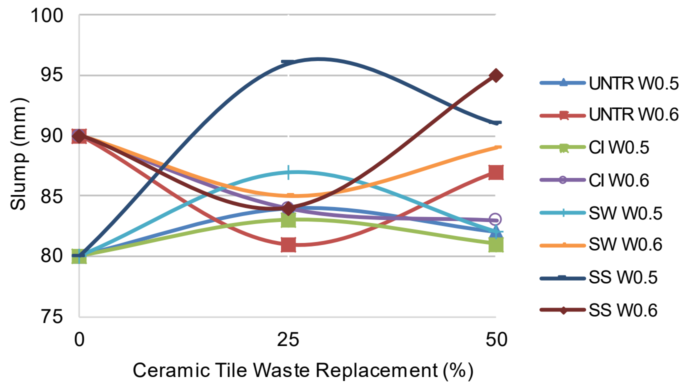

Fig. 3. Slump test results.

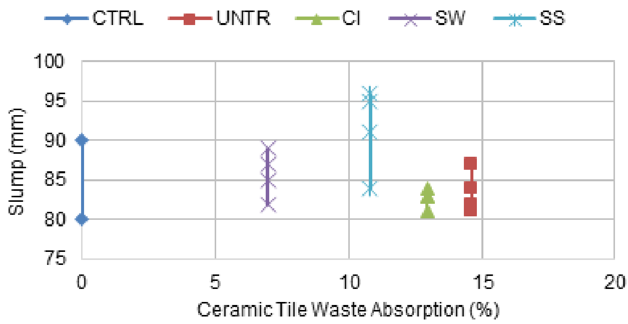

Fig. 4. CTW absorption rates and slump based on AMT method.

3.3. Compressive strength test results

Compressive strength tests were performed on all specimens using the Universal Testing Machine of De La Salle University, Manila, Philippines, in accordance with ASTM C39M. The Universal Testing Machine was pre-calibrated and operated by the qualified professional of De La Salle University, Manila, Philippines. After obtaining the test results for each concrete batch, an outlier test was conducted as part of the data treatment in the study. Consequently, all outliers were eliminated in the study's data set for analysis. After obtaining the results, Modified Z-Score Outlier Test was done to remove any inconsistencies that affected the trends within the data. This specific outlier test can be applied to a data set that has a small number of samples. Out of the 108 cylinders that were tested, a total of 13 samples were deemed as outliers and were excluded in the analysis of data [34]. Figure 5 summarizes the results of compressive strength tests at the specified age of curing period.

The target nominal strengths were 27.97 MPa and 21.97 MPa for batches with 0.5 and 0.6 w/c, respectively. These were based on ACI standards, depending on the w/c ratio used. Nominal compressive strengths are typically used by structural engineers in designing concrete structures, unless cured concrete is required earlier than 28 days.

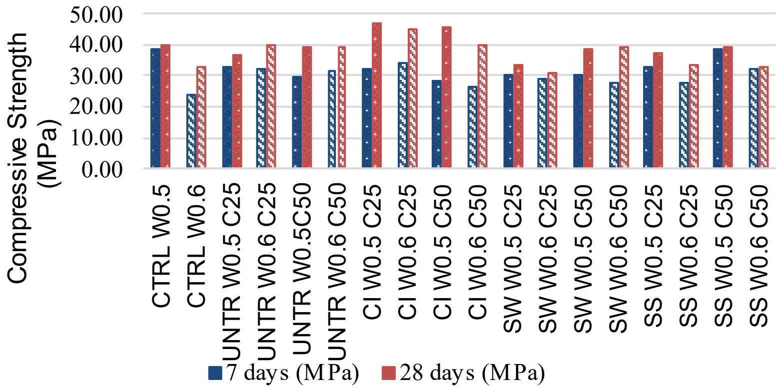

Fig. 5. Graphical illustration of average compressive strength test results.

Considering that the lowest measured nominal compressive strength among all specimens is 31.17 MPa (SW W0.6 C25), it was determined that all concrete mixtures achieved, and even surpassed the target nominal strengths. This indicates that regardless of the water-cement ratio considered, the inclusion of AMT methods and CTW aggregates in the concrete mix was found to be beneficial on the compressive strength.

Furthermore, the compressive strengths of batches with 0.5 w/c ratio, having either untreated or treated CTW aggregates, were generally lower than the control batch for both curing periods of 7 and 28 days, excluding the mixes that incorporated CI treatment. The concrete mixture, treated with CI and had 0.5 w/c ratio, had a nominal compressive strength of 46.68 MPa (CI W0.5 C25), which was 6.67 MPa greater than that of the control specimen. On the other hand, the compressive strengths of mixes with 0.6 w/c ratio were generally greater than the control batch, except for SW W0.6 C25, which had a difference of -1.48 MPa when compared to CTRL W0.6. Previous studies have shown that increasing the water content in the conventional concrete mixture results to a decrease in concrete bond and compressive strength [35]. This is because excess water generates space between the aggregates, and when such excess water evaporates after concrete pouring, the voids are filled with air, resulting to poor compaction of the aggregates thereby resulting to poor concrete bond and strength. However, the said typical effect of water content in the conventional concrete mixture was generally not observed in this study. This is highly likely due to the high absorption rate of the CTW aggregates, where the excess water content was absorbed by the CTW aggregates, reducing the potential voids between the concrete aggregates.

The AMT methods were part of the variables investigated in this study. Among the 3 AMT methods employed, CI treatment was found to be the most beneficial. The concrete mixes that incorporated CI treatment method yielded compressive strengths ranging from 39.81 MPa (CI W0.6 C50) to 46.01 MPa (CI W0.5 C25). Relative to the control mix, the early strength of the mixes with CI treatment on the CTW aggregates generally produced lower compressive strengths. However, all nominal strengths of the same mixes surpassed the compressive strengths of both the control mix and the mix with untreated CTW aggregates. This increase in compressive strength is due to the filling of aggregate voids, as shown in the decrease in absorption, and the formation of a cement coating around the coarse CTW, thereby efficiently supplementing the aggregate through modifying its properties. Other similar studies have also observed such positive effect of CI treatment on aggregates, claiming that following the setting process under the impregnation solution, durable layer was formed on the surface of the impregnated aggregates. The CTW aggregates were essentially sealed with adhered mortar, which likely increased the specific surface area, thereby reducing the voids within the concrete matrix [11].

3.4. Strength development results

The strength development of each mix was measured through the results obtained from testing the compressive strength of the concrete specimens after 7-day and 28-day of curing periods. The average strengths of the concrete specimens tested after 7 days and 28 days of curing period correspond to the early and nominal strengths of the mix, respectively.

The order of AMT methods that resulted to the least to greatest improvement on the compressive strength is as follows: control samples (no CTW, no treatment), sodium silicate soaking, untreated CTW, slurry wrapping, and cement impregnation. The sample with the highest amount of strength increase of +17 MPa is observed among the CI batches, specifically CI W0.5 C50, while the least improvement of only +0.72 MPa is found among the SS batches, specifically SS W0.6 C50. Figure 6 shows the diagram of strength development in this study.

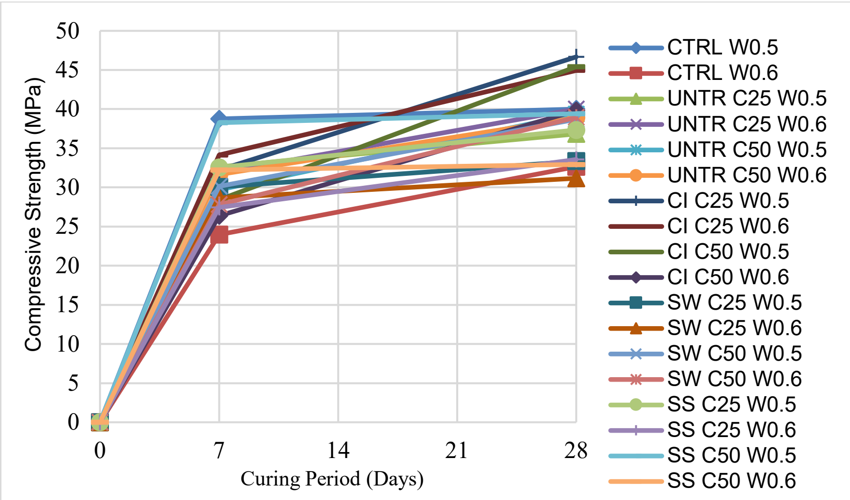

Fig. 6. Summary of strength development results.

As seen on Fig. 6, the control mix with 0.5 w/c produced the highest early strength with 38.77 MPa after 7 days of curing period. This was followed by the mix with 50% CTW aggregates that underwent SS treatment and 0.5 w/c, having 38.27 MPa, which is slightly lower than that of the control mix. These mixes are beneficial on time-sensitive construction projects that depend on the immediate curing of concrete. However, in terms of the nominal compressive strength, those mixes were surpassed by the mixes with CTW aggregates that had CI treatment, except for the mix with

50% CTW aggregates and 0.6 w/c. On the other hand, the control mix with 0.6 w/c produced the lowest early strength with 23.99 MPa. Generally, in terms of the modified mixes, the mix with CTW aggregates that underwent SS and SW treatment methods also produced low early and nominal compressive strengths. These suggest that under the parameters considered in this study, the mixture of cement and water, was the best treatment method, as opposed to the mixture with cement, water and a pozzolanic substance, and 8% sodium silicate.

3.5. Decision tree regression (DTR)

The CART model was produced using Python, where the input parameters are the AMT, CWT, w/c and curing days, and the output results are the compressive strength. Table 6 summarizes the parameters used in generating the decision tree model:

The DTR model input variables are designed to be quantitative. The input parameters were assigned legends A, B, C and D to correspond to AMT, CTW Replacement, w/c and days of curing, respectively. To incorporate AMT to the DTR model, each treatment was assigned an arbitrary number, where is the Untreated concrete, 1 is the concrete with cement impregnation, 2 is concrete with slurry wrapping and 3 is concrete with Sodium Silicate Soaking.

The output parameter for the model is the compressive strength obtained from the experimental results. The input and output parameter parameters were randomly split into 70% train data and 30% test data. The train data was used to train and create the DTR model, while the test data was used to validate the model. The validation was done to check whether the produced DTR model is still consistent with the test data.

Table 6. Input parameters for decision tree.

Legend	Description	Input	
A	Aggregate Modification Treatment	0	Untreated
		1	Cement Impregnation
		2	Slurry Wrapping
		3	Sodium Silicate Soaking
B	CTW Replacement	0.00	0%
		0.25	25%
		0.50	50%
C	W/C	0.5	
		0.6	
D	Days of Curing	7	
		28	

Using the parameters shown in Table 6, a decision tree model was constructed considering different number of leaves, ranging from 2 to 9. The splitting of each nodes used the reduction of variance method. The model identifies which parameter greatly affects the variance and the DTR would split the samples to reduce the variance. This was done until the tree was optimized based on the RSME and R^2.

The resulting RSME and R^2 values of each model tested were recorded to determine the best DTR model. Figure 7 shows the summary of the said RSME and R^2 values.

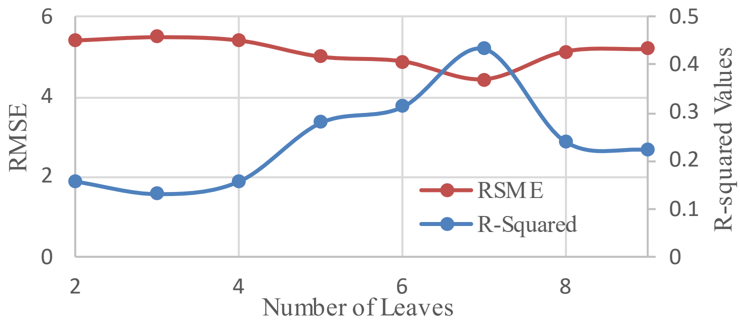

Fig. 7. RSME and R^2 values of different models tested.

Based on the results shown in Fig. 7, as the number of leaves increased, the corresponding RMSE decreased up to the model with 7 leaves. The models with 8 and 9 leaves resulted to higher RSME than the one with 7 leaves. Conversely, the R^2 value was increasing, as the number of leaves was increased up to the model with 7 leaves. The models with 8 and 9 leaves resulted to lower R^2 value than the one with 7 leaves. Because of these, it was determined that the best DTR model was the one with 7 leaves, with RMSE and R^2 of 4.43 and 0.44, respectively. Based on Pearson's correlation interpretation criteria, the model's R-squared value suggests that there is a strong correlation between the actual and predicted test results [36]. This further validates the acceptability of the DTR model generated as shown in Fig. 8.

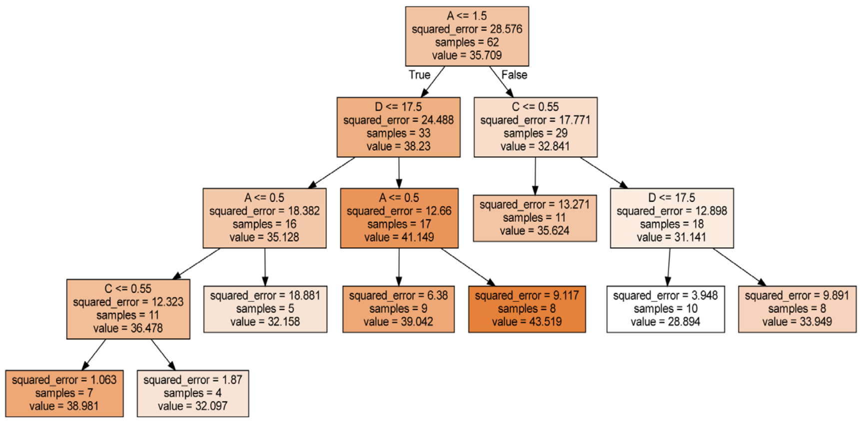

Fig. 8. Decision tree model.

The DTR model shows that there are 3 principal components among the input parameters, which are the AMT (A), w/c (C), and days of curing period (D). The said 3 principal parameters are considered relevant in predicting the compressive strength. Among the principal parameters, the AMT is considered as the most impact to the prediction, as seen on the topmost leaf node of the tree model. This suggests that AMT has a considerable effect on the compressive strength, relative to w/c, and CTW percentage replacement. After the AMT, the w/c and number of curing days are the next most significant variables based on the model. This indicates that the interaction between the w/c and AMT has a relevant impact on the compressive strength of the concrete mix. On the other hand, the number of curing days is expected to serve as a relevant parameter in predicting the strength, noting that the nominal compressive strength is expected to be higher than the 7-day early stage of concrete. Although the CTW percentage replacement has an impact on the compressive strength, the said parameter does not appear to be a relevant variable among all input parameters. This indicates that the AMT and w/c of the concrete mix have more impact in predicting the compressive strength than the amount of CTW replacement.

The DTR model showed that the AMT is CI and cured after 28 days, it would produce the highest expected nominal strength. The results from the model showed that the w/c and amount of CTW replacement did not impact the expected outcome. The results also showed that the amount of CTW replacement does not affect the compressive strength outcome in the combinations, as this parameter did not appear in the DTR model.

4. Conclusion and Recommendations

This study aims to determine the impact of utilizing waste ceramic tiles in concrete through replacing conventional coarse aggregates. The replacement of CTWs was limited to 25% and 50%. However, similar studies have shown that the high absorption rate of the CTWs affects the workability, and potentially the compressive strength of concrete. As such, this study further evaluated the effect of varying the water-cement ratio and incorporating aggregate modification treatments in the mix. The water-cement ratio considered in this study was 0.5 and 0.6. On the other hand, the aggregate modification treatments were slurry wrapping, sodium silicate soaking, and cement impregnation. Summarized below are the findings of the study:

- When no aggregate modification treatment was introduced on the waste ceramic tiles, all concrete mixtures with 0.6 w/c had higher compressive strengths than the control mix. On the other hand, all mixes with 0.5 w/c had lower compressive strengths than the control mix. These results are not in line with the conventional concrete, where the compressive strength decreases as the w/c is increased due to the voids filled by the excess water in the concrete mix, which evaporates over time. This is highly likely due to the high absorption rate of the CTW aggregates, where the excess water content was absorbed by the CTW aggregates, reducing the potential voids within the concrete matrix.
- The aggregate modification treatments used in this study were found to be effective in decreasing in absorption of the ceramic tile waste aggregates that reduces both the workability of the concrete mix, and the resulting compressive strength.
- Among all mix designs, the concrete mix with Cement-Impregnated treatment had the greatest nominal compressive strengths. The mix with 25% waste ceramic replacement and 0.5 w/c produced the best results with 46.68 MPa nominal compressive strength, which was about 16.7% stronger than the

control mix. The said modified mix may be pursued as an alternative to structures that require normal strength concrete. The observed positive effect of CI treatment on aggregates is highly associated to the setting process under the impregnation solution, where durable layer was formed on the surface of the impregnated aggregates. The CTW aggregates were essentially sealed with adhered mortar, which likely increased the specific surface area, thereby reducing the voids within the concrete matrix, and strengthening the concrete. On the other hand, the concrete mix that considered slurry wrapping treatment generally resulted to a reduction in compressive strength relative to the mix with untreated ceramic aggregates. This suggests that SW treatment may not be an effective method in treating CTWs in concrete.

- The generated DT model was able to determine which combination of parameters produces the optimum compressive strength. Based on the decision tree model generated, the aggregate modification treatment was found to be the most influential factor in predicting the compressive strength.
- Using the reduction of variance method, the DTR model identified the most influential parameter as the variable affecting high variance.
- The DT model also showed that the amount of CTW replacements do the impact the compressive strength as much as the other parameters. This can be interpreted that CTW replacements has no significant impact to the compressive strength making it a good alternative to coarse aggregates.
- The DT model showed consistency with the experimental results. It also showed that the curing days also greatly impact the compressive strength after the AMT, followed by the w/c ratio. The model also showed the impact of each parameter affect one another.

To improve the study, it is recommended to:

- Extend the soaking time to one day when incorporating slurry wrapping and sodium silicate treatment methods to produce a more concentrated treatment process of the CTW aggregates.
- Considering the individual performance of the concrete mixes after 7 days of curing period, test the concrete samples after 1 day of curing period to determine whether they meet the criteria for high early strength concrete. Additionally, consider extending the curing periods of concrete to have a better understanding of its strength development, noting the possible pozzolanic reaction when CTWs and aggregate modification treatments were introduced in the concrete mix.
- Test other mechanical properties of concrete to further support the feasibility of utilizing CTWs in concrete. These other mechanical properties include density, flexural strength, shear strength, tensile strength and many more.
- Conduct a cost-benefit analysis, incorporating the life cycle assessment of all materials used, to determine the sustainability of utilizing CTWs in concrete, despite introducing aggregate modification treatments. Additionally, product acceptance surveys on the stakeholders, such as construction companies, concrete manufacturers, and developers, may be conducted to determine the viability and acceptance in the market of incorporating treated CTWs in concrete.

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