A Prediction Model for CO 2 Concrete using Regression Analysis and Artificial Neural Networks

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Abstract

Concrete is a very effective material for the construction of buildings and infrastructure around the world. Unfortunately, typical concrete is a large contributor to CO_2 emissions and consumption of natural reserves. CO_2 Concrete allows the mitigation of these downfalls by carbonating recycled aggregate, reducing CO_2 emissions, reusing crushed masonry materials and conserving virgin aggregate. CO_2 Concrete can also be considered reliable as its compressive strength can be accurately predicted by both regression analysis and artificial neural networks. The artificial neural network created for this paper allow accurate prediction of the compressive strength for CO_2 Concrete. The artificial neural network exhibited a strong relationship with the experimental specimens, revealing a multiple R of 0.98 and an R square of 0.95. The artificial neural network was also validated by 22 laboratory validation concrete mixes. The artificial neural network displayed an average error of 1.24 MPa or 3.43% in the validation mixes with 59% of concrete samples within 3% error and 77% being within 5% error. The successful prediction of compressive strength of CO_2 Concrete can help a greater mainstream use of the green material.

Background

Applications of prediction models for conventional concrete and recycled concrete are very important in the reliable widespread utilisation of material. Prediction of parameters is vast and typically includes significant qualities of concrete including compressive strength, flexural strength, CO_2 uptake and chloride ion permeability [1–3]. Mathematical prediction of concrete quality and variables can be completed with techniques such as regression analysis and more recently various artificial neural networks. The employment of such techniques has yielded great success in the prediction of important parameters of concrete, implying that concrete employing new technologies and materials can be used reliably in real life circumstances [4, 5].

Concrete is a robust and versatile material that is characterised by widespread use around the world. However, environmental effect and sustainability of concrete is a worrying issue. Concrete requires vast amounts of natural resources, predominantly aggregate from quarries with a worldwide production of aggregate reaching 40 billion tonnes in 2014 [6].

Construction and demolition waste, comprises of material such as metal, concrete, mineral, masonry, glass, wood waste and other small amounts of various waste [6, 7]. Construction and demolition waste and in particular masonry waste, the largest portion, contributes to a large percentage of land filling globally. In many countries masonry waste, by weight, is one of the largest contributors to landfill [6, 7].

Cement, the binder of concrete is responsible for 5–7% of the planets annual CO_2 emissions [8, 9]. The poor environmental performance of concrete has led researchers to conduct studies in which more environmentally friendly or ‘green concrete’ has been investigated. Green concrete studies have one or more common aims, conserve natural resources, reduce landfill space taken by masonry waste and/or reduce CO_2 emissions [10–12]. However, in generating alternative concrete an uncertainty to the performance is created, as an alternative concrete does not have the same amount of regular usage as conventional concrete.

The regression analysis or creation of an artificial network for the prediction of compressive strength of CO_2 Concrete has yet to be studied. Therefore, this paper develops the prediction models of CO_2 Concrete quality using regression analysis and artificial neural networks. Elements of carbonation of cementitious materials have been modelled, including aspects such as rate at which cement is carbonated under pressure [13]. This paper introduces

new knowledge with the production of an artificial neural network for the prediction of compressive strength of CO_2 Concrete considering carbonation and concrete mix design variables.

Modelling Techniques For Concrete Prediction

Regression Analysis

Regression analysis allows the prediction of a selected concrete quality through the generation of a mathematical formula. Regression analysis comprises of a dependent variable, the quality that is to be predicted, and independent variables, which effect the result of the dependent variable [14]. Independent variables are given a mathematical constant depending on how much each variable effects the dependent variable. Younis and Pilakoutas [15] utilised multi-linear regression analysis to predict the dependent variable of compressive strength of recycled aggregate concrete by using independent variables applied with appropriate constants including dry aggregate particle density, water absorption, resistance to fragmentation and recycled aggregate ratio.

Artificial Neural Network

The application of artificial neural networks in the prediction of important concrete characteristics has become popular over the last decade [16,17]. Artificial neural networks simulate the prediction and recognition function of the biological brain to solve problems of a complex nature [18].

The human brain can recognise complex non-linear problems in a very short time. The speed of computation can be attributed to three simplified layers. The first process involves the gathering of information, either through sight or other senses. This information is then transferred to the neurons, which have been trained. The activation of a trained conglomerate of neurons helps utilise stored algorithms, which permit, in stage three, the recognition of, for example, the shape of a letter or number [18].

Artificial neural networks apply the same logic of three layers. The first layer is the input layer of the artificial neural network where known data is entered into the network. Depending on the parameters that is to be predicted, appropriate input variables are selected. For example, Naderpour, et al. [19] created an artificial neural network that has input nodes of water-to-cement ratio, water absorption, fine aggregate, recycled coarse aggregate, natural coarse aggregate and water-total material ratio for the prediction of the compressive strength for recycled aggregate concrete.

After data is entered into the input layer it then goes to the hidden layer, which is the equivalent of the human brain section that stores the algorithms. Certain nodes activate based on the learning the network has undergone in response to the input layer nodes. The hidden layer can be made up of multiple layers of nodes, depending on the amount of information and the accuracy of the prediction [18,19].

The last layer is the output layer, which predicts the desired variable based on the input variables as well as the hidden layer containing the trained knowledge [18,20].

Alternative Concrete Prediction Models

The applications of prediction techniques and models have been used in conjunction with alternative environmentally friendly concrete to ensure reliability of the concrete and to provide possible consumer confidence in a new product.

Prediction of Recycled Aggregate Concrete

Recycled aggregate concrete can utilise ceramic wastes such as concrete and brick as a replacement of virgin aggregate from quarries [21]. The employment of crushed concrete, brick and tile can help mitigate the amount of demolition waste that is sent to landfill. Unfortunately, the complete replacement of virgin aggregate with recycled aggregate in concrete reduces the compressive strength by 30% [22,23]. The poor quality of the recycled material has largely prevented widespread use in replacement of virgin aggregate concrete. However, researchers have successfully been able to produce prediction methods and models for recycled aggregate concrete.

A predominant technique for the prediction of recycled aggregate is the creation of an artificial neural network. Artificial neural networks have provided excellent accuracy in predicting recycled aggregate concrete properties [19]. Table 1 provides the R^2 of past researchers best artificial neural network after training for the prediction of key qualities of recycled aggregate concrete.

The closer the R^2 value is to 1, the higher the correlation. Table 1 shows that artificial neural networks have a strong ability to predict qualities, predominantly compressive strength, as the R^2 value is very close to 1 after training for prediction. The use of various artificial neural networks has largely surpassed regression analysis predominantly due to accuracy [19]. The accuracy of artificial neural network for the prediction of concrete containing recycled products can be considered very accurate.

Prediction of Concrete Containing Recycled Rubber

The replacement of fine and coarse virgin aggregate can be made with recycled tire rubber. The replacement permits the conservation of natural resources and permits tires to be recycled rather than contributing to waste streamlines [24]. Unfortunately, with greater amounts of rubber replacement, concrete experiences a reduction in mechanical quality with researchers specifying that as low as 20% rubber replacement having a detrimental effect on compressive strength of concrete [25-27]. However, researchers have investigated predictive models for recycled rubber concrete. Table 1 provides the correlation of the authors most accurate artificial neural networks after training in the prediction of the compressive strength of recycled rubber concrete.

The correlation of the artificial neural network for the prediction of compressive strength is very strong showing that the compressive performance of recycled rubber concrete is predictable [28,29]. The accuracy shows that recycled rubber concrete can reliably be used, however, only at certain replacement contents for fine and coarse aggregate.

Prediction of Concrete Containing Recycled Glass

The employment of recycled crushed glass as fine or course aggregate and cement has been researched over previous studies [30-32]. Ghorbani, et al. [30] highlights that the application of recycled glass as a partial replacement as fine aggregate or cement can increase the compressive strength of concrete. However, the addition of glass is known to accelerate the alkali-silica reaction which must be mitigated by the addition of admixture chemicals or

mineral admixtures [33]. The replacement of virgin materials for glass offers the ability to reduce glass waste and as a result, researchers have created prediction models to show that the material can be consistent. Table 1 shows the R^2 correlation of the commonly preferred artificial neural network prediction.

Table 1 shows that various recycled aggregate substitution in concrete can be completed with accurate prediction. Table 1 shows a correlation of close to 1 meaning the accuracy of artificial neural networks is very precise.

Limitations and Opportunity of Recycled Materials in Concrete

Recycled aggregate, rubber and glass all offer the opportunity to conserve natural resources while producing a concrete product. Furthermore, strength of recycled concrete can be predicted with great accuracy with the assistance of procedures such as artificial neural networks. However, the principal factor for the limited use of such materials is the performance, cost and impracticality compared to traditional concrete [24,34,35]. Many studies have aimed to increase the performance, reduce costs, and increase practicality over recent years. A supplementary strengthening measure of injecting carbon dioxide (CO_2) into recycled aggregate concrete has yielded positive outcomes [36-38].

The injection of CO_2 into recycled aggregate densifies the recycled material by converting calcium hydroxide in calcium carbonate. The chemical reaction also permanently removes the involved CO_2 [39,40]. Equation 1 shows the fundamental chemical reaction.

Equation 1: $Ca(OH)_2 + CO_2 = CaCO_3 + H_2O$

Many researchers have shown that carbonated recycled aggregate concrete or CO_2 Concrete can rival virgin aggregate concrete in mechanical properties while also using recycled aggregate and removing CO_2 [12,38,41]. However, there are opportunities to further research, particularly in the prediction of compressive strength of CO_2 Concrete.

Results And Discussion

Comparison between Regression Analysis, Artificial Neural Network and Laboratory Data used for the Developed Predictive Models

Though both the prediction models of multiple regression and artificial neural networks are invaluable, the better of the two must be determined to reveal the suitable prediction methodology for CO_2 Concrete. The techniques can be evaluated based on successful prediction as well as the errors relative to laboratory results. The analysis compares the accuracy of the prediction models against the 61 data points used to create them (creation dataset). Table 4 presents some general statistics for accuracy analysis, both the error and R values when applied to laboratory specimens used to create them and compressive strength results and error.

Standard Deviation

Table 4 reveals the tremendous performances of both regression and artificial neural networks relative to the laboratory data. Regression yielded the smallest standard deviation, with all the results being close to the mean. The artificial neural network followed the regression, with the laboratory results characterised by the highest standard deviation. Table 4 indicates that regression yields the best results; however, Table 4 displays how artificial neural networks can subvert the standard deviation and provide a superior prediction of strength [1].

Error

Error, in the context of strength prediction, allows for observation of the accuracy of the predicted value when compared with the laboratory data [18]. Consequently, the investigation of error permits evaluation of the forecasting ability of both regression and artificial neural networks. Table 4 indicates excellent performances of both the strength prediction methodologies, with the procedures exhibiting small errors.

The artificial neural network achieved less error than the multiple regression method. The difference in errors is most evident when considering the mean absolute percentage error, with multiple regression analysis showing a value of 4.01, whereas artificial neural networking displays almost half the error (2.33).

The reduction in the error of the artificial neural network has been confirmed by earlier researchers [1,20,42]. The accuracy of artificial neural networks in research papers over the years has also reinforced that the process can be more accurate than regression analysis [29,43]. The ability of the artificial neural network to deliver only a small error is concealed in the hidden layer and reflects the learning ability of the network [1]. The network can analyse the trends in the laboratory results from many different aspects, which permits a deeper relationship with real specimens. Training the network optimally, by not underfeeding or overfeeding, also helps in the elimination of error. The utilisation of artificial neural networks results in a better performance in terms of error prediction when compared to regression analysis and, consequently, can be superior.

Multiple R and R Square

Multiple R as well as R square reflects the correlation between regression analysis and artificial neural networks, when compared with the experimental laboratory data [14]. The closer the value to 1, the greater the correlation between the model and the test product [18]. Table 4 exhibits a substantial correlation, with the regression analysis achieving a multiple R of 0.94 and an R square of 0.88. The artificial neural network registered a stronger correlation than regression analysis, revealing values of 0.98 and 0.95 for multiple R and R square respectively.

Similar to the reduction in error, the strong correlation can be attributed to the ability of the artificial neural network to learn as well as apply the learning to the prediction of concrete strength [1]. Consequently, artificial neural networks can solve complicated non-linear problems as the relation between certain variables can be recognised and compared [20]. The prediction of the compressive strength of CO_2 Concrete can be complicated, which renders the artificial neural network the preferred choice.

The high R values indicate that the artificial neural network excels at prediction of the compressive strength of concretes. The strong correlation can be utilised in the prediction of compressive strength, which reduces the requirement for future laboratory mixes in addition to targeting of strength for future concrete batching. The

methodology of artificial neural networking provides an excellent insight into CO_2 Concrete. However, verification of the method is required.

Verification of the Artificial Neural Network for the Prediction of Compressive Strength of CO_2 Concrete

Table 4 provides the error experienced by the artificial neural network on the prediction of the 22 verification laboratory data points (verification dataset). Unlike, checking the accuracy of the artificial neural network against the laboratory mixes used to create the network, the artificial neural network will be compared to the verification data set (21 data points) rather than the creation dataset (61 data points).

The artificial neural network created revealed an outstanding accuracy, with the average error being 1.24 MPa or 3.43%. The precision of the network can be attributed to the ability to solve complex non-linear problems, aptitude for learning and addition of many hidden layers for the consideration of subtle characteristics. Table 4 as well as past investigations confirms that the compressive strength of concrete is predictable as a consequence of the characteristics of artificial neural networking. [1,20]. Table 4 further reveals that CO_2 concrete is easily foreseeable.

The artificial neural network did, however, exhibit a maximum error of 10%, which was followed by an error of 7.91%, for the samples 0.45/50-90-115 and 0.45/70-105-135, respectively. The maximum error is not a reflection of the inaccuracy of the neural network, but an indication of the variations in the recycled aggregate concrete itself. Unfortunately, the nature of mixed recycled aggregate implies outlying outcomes are possible. The possibility of either soft organics or denser materials allows for either additional weakening or strengthening of CO_2 Concrete [21,44]. In the case of the 0.45/50-90-115 concrete, a larger portion of the aggregate contained either organic material or subpar aggregate. Contrastingly, the 0.45/70-105-135 CO_2 Concrete experienced an outlying gain as a result of the presence of denser materials in mixed recycled aggregate, such as basalt. The current measures for quality control of mixed recycled aggregate result in the retention of undesirable materials [21]. However, generally, there is only a small mass of unwanted material, which does not affect the entire concrete to a great extent. Though the artificial neural network is extremely accurate, the current recycled aggregate standards of material permit rare poor samples, the results of which are 10% off the predicted value. The artificial neural networks can exhibit greater precision only if the undesirable materials are completely eliminated. The poor-quality material found in mixed recycled aggregate cannot be modelled as it is completely randomised during the creation stage.

Artificial neural networking can be considered as an extremely accurate forecasting strategy, as a great number of concrete samples exhibit very similar errors. The largest error of 10%, whilst significant, is also an indication of the realistic error of concrete itself. The many factors involved in the realisation of the final compressive strength of a concrete can very easily produce an even larger error [45].

The small average error of 3.43% provides remarkable evidence for the fact that the artificial neural network exhibits a strong correlation with CO_2 Concrete; the properties of CO_2 Concrete are therefore predictable. Table 4 reveals that 59% of laboratory specimens presented errors which were less than 3%, whereas 77% of the CO_2 Concretes exhibited an error below 5% and 91% of the real-life samples revealed errors which were centred at 7.5%. As researchers have explained, it is extremely accurate for 60% of the data to be within 7.5% error limit and 95% of the data to be within 20% error limit in the case of recycled aggregate concrete [1]. Accordingly, it can be confirmed that the compressive strength of CO_2 Concrete exhibits an extremely strong correlation with the artificial neural network.

The predictability combined with the additional strength delivered by injection of CO_2 into aggregate allows for the realisation of a practical final concrete. The process by which recycled aggregate is injected with CO_2 is not complicated or difficult to execute. The ease of execution, in combination with the predictability of CO_2 Concrete, allows for a recycled product with repeatable characteristics. CO_2 concrete presents future product.

Conclusion

This paper developed the prediction model for compressive strength of CO_2 Concrete using regression analysis and using artificial neural networking. The ability to predict the compressive strength of new concrete types is very important to ensure the reliability of a material such as CO_2 Concrete. The employment of regression analysis and the creation of an artificial neural network assist in ensuring that CO_2 Concrete is reliable. The creation of the prediction models against the 61-laboratory data set showed close correlations. The regression analysis exhibited multiple R of 0.94 and an R square of 0.88 with the laboratory results. The artificial neural network exhibited a strong relationship with the experimental specimens, revealing a multiple R of 0.98 and an R square of 0.95. Furthermore, the validation of the artificial neural network with 22 additional validation concrete mixes provided accurate results. The artificial neural network displayed an average error of 1.24 MPa or 3.43% when compared with CO_2 concrete. 59% of the CO_2 concrete exhibited less than 3% error when compared to the prediction of the artificial neural network. 77% of the 22 CO_2 concrete samples were localised within the 5% error interval relative to the prediction of the artificial neural network. 91% of the samples displayed a great accuracy, the values being within 7.5% of the predicted values. CO_2 Concrete combined with the accuracy of artificial neural network prediction can allow for the potential of a green concrete that may have additional widespread use.

Methods

Development of CO_2 Concrete Predictive Models

The creation of predictive models requires a laboratory data set. Consequently, 61 different concrete variations are produced for the generation of both regression analysis and artificial neural network.

Materials for Concrete

Recycled Aggregate

The recycled aggregate used for the generation of concrete originates from a centralised recycling plant in south-eastern Australia. The recycled aggregate is graded to 10 and 20mm. Figure 1 shows a classification breakdown of the recycled aggregate.

Virgin Aggregate

The virgin aggregate used in this paper is basalt and is supplied by a south-eastern Australia centralised plant. Basalt is required to allow for the varying recycled aggregate replacement percentages. Figure 1 shows both the virgin aggregate and recycled aggregate.

Sand

The sand employed within this paper is obtainable from a south-eastern Australia supplier. The apparent particle density, particle density on dry basis, particle density on saturated surface-and dried basis are 2.67, 2.53 and 2.58 tonnes per m^3 respectively. The water absorption is 2.20%.

Cement

The cement used in the creation of concrete for the generation of predictive models is a general blended cement. The cement contains 30% fly ash and conforms with AS.3972-2010 [46] General purpose and blended cements.

CO_2

CO_2 is supplied from an Australia wide supplier and is industrial grade which has gas purity greater than 99.9%.

Admixtures

No chemical admixtures are used in the creation of concrete for this paper.

Carbonation Chamber

The carbonation chamber employed in the CO_2 injection into recycled aggregate is rectangular shape, sized at 500 mm x 500 mm x 300 mm. The pressure of the CO_2 is controlled with the assistance of a gas pressure regulator connected at the inlet valve. A relief valve is used to vent other gases while CO_2 is injected into the chamber. Aggregate is carbonated at a natural moisture content. Silica gel is also added into the chamber to ensure there is no water accumulation due to the carbonation reaction. Figure 2 provides an image of the chamber design.

Concrete Testing, CO_2 Concrete Variables and Mix Design for Generation of Prediction Models

Compressive Strength Testing

The creation of concrete specimens for laboratory compressive strength testing is required to allow for regression analysis as well as the creation of an artificial neural network. Three 100-mm-diameter and 200-mm-height concrete cylinders were utilised in the determination of compressive strength. The pouring of samples is completed in accordance with AS.1012.2 [47].

Compressive strength is obtained with the assistance of a hydraulic press and is completed in accordance with AS.1012.9 [48]. Upon 28 days, the 100-mm-diameter and 200-mm-height concrete cylinders are either capped or ground on the flat surface to ensure uniform loading. The cylinder is then placed within the press and compressive load is applied at a rate of 20 ±2 MPa per minute until failure.

CO_2 Concrete Variables

The CO_2 Concrete experimental program includes several variables which allow for different compressive strength quality. The variables include water to cement ratio, recycled aggregate replacement ratio, carbonation pressure and carbonation duration. The variables can be observed in Table 2.

Experimental Design

Based on the given variables 61 different concrete mixes or data points are created (creation dataset). Each data point or mix design is given a mix code. The mix code reads water to cement ratio/recycled aggregate-replacement-carbonation-duration-carbonation pressure. Table 2 provides all variables of the 61 data points.

Mix Design

The mix design allows for a direct comparison of water to cement ratio, recycled aggregate replacement and carbonation variables. Aggregate is mixed into concrete at a saturated-surface dry state to ensure that a fair comparison can be made. Table 2 shows the mix design for concrete samples used for regression analysis and artificial neural networking.

Laboratory Concrete Results for Generation of Prediction Models

All compressive strength results are an average of three results. Figure 3 splits into three mains sections, isolating water to cement ratio. With the separation of water-to-cement ratios, the recycled aggregate concrete replacement and carbonation variables can be compared to the control sample. The control sample bars are coloured in black, 30% recycled aggregate replacement coloured in blue, 50% recycled aggregate replacement coloured in red and 100% recycled aggregate replacement coloured in green. Figure 3 shows that the injection of CO_2 can help greatly as the samples without carbonation are amongst the lowest in strength. For example, without carbonation the 100% recycled aggregate replacement sample (0.4/100-0-0) achieved a strength of 33.14 MPA while the carbonated concrete, 0.4/100-120-75 averaged 39.64 MPa and 0.4/100-120-25 achieved 39.33 which is a near 20% improvement. Furthermore, if the 100% samples with 0.45 and 0.5 water to cement ratios are observed the carbonated samples experience an even greater increase in compressive strength over the untreated samples. The 61 data points found in Figure 3 are used for regression analysis and the artificial neural network creation. The results are also published in the following paper [38].

Development of the Predictive Models based on CO_2 Concrete's Compressive Strength

Regression Analysis

By utilising the 61 statistical points (creation dataset) from the data array a regression analysis formula can be generated. The formula permits a multiple regression analysis based on seven key variables, which determine the compressive strength of CO_2 Concrete. When applied with constants Equation 2 can be employed for determining the compressive strength of CO_2 concrete.

Equation 2: Multiple Regression Formula for Determining the Compressive Strength of CO_2 Concrete

$$F'_c = -10089.538 - (R_{wc}) - (R_{rca}) + (C_{p1}) + (C_{p2}) + (Q_c) + (Q_w) - (Q_{sand})$$

The key variables in the formula are the compressive strength (F'_c), water-to-cement ratio (R_{wc}), recycled coarse aggregate replacement ratio (R_{rca}), carbonation pressure (C_{p1}), carbonation duration (C_{p2}), amount of cement (Q_C), quantity of water (Q_w) and volume of sand (Q_{sand}).

Artificial Neural Networks

The artificial neural network is created using MATLAB and involved training multiple hidden layers to obtain precise results. An artificial neural network containing multiple hidden layers allows for a greater number of nodes and, therefore, can recognise complicated non-linear problems [18]. The advent of multiple hidden layers allows for a reduction in error when forecasting the compressive strength of CO_2 Concrete [1]. Figure 4 shows two input screens for the created artificial neural network. The input windows permit (A) the prediction of compressive strength based on CO_2 Concrete variables or conversely, (B) possible mix designs of CO_2 Concrete based on a desired compressive strength.

Verification of the Developed Models

The accuracy of a prediction model can be compared for accuracy against existing laboratory compressive strengths, however, the generation of new concrete for the validation of such predictions is very important to endorse the accuracy of a given prediction model. Consequently, variables between the variables utilised in the production of prediction models can assist in evaluating the success of predictive model.

CO_2 Concrete Variables for Verification of Predictive Model

Table 3 shows the verification variables in between the variables used for the creation of mathematical models.

Experimental Design for Variation of Predictive Model

The experimental design utilised partially randomised carbonation variables which largely corresponded to the high-pressure range 100 to 200 kPa and long durations of 50 to 120 min. The selected carbonation variables permit new data to be obtained in new intervals. The verification data lies between the 75 and 200 kPa arrays, which allows for forecasting of the compressive strength without the use of the same variables to create the model to verify the prediction model. Each result obtained is an average of three separate results.

The water-to-cement ratio as well as the recycled aggregate replacement ratio exhibits a smaller variation than the carbonation variables. The selection of three water-to-cement ratios and recycled aggregate replacement ratios mirror a real-life or practical design. Changes in either of these variables require a slightly different mix and therefore would not be practical for implementation.

The validation data including 22 (validation dataset) different concrete mixtures assist in the investigation of validation of predictive model against CO_2 concrete itself. When interpreting the mix code, the first number refers to the water-to-cement ratio, the second represents recycled aggregate replacement percentage, the third reveals the carbonation duration and, finally, the fourth specifies the carbonation pressure. Table 3 presents the concrete utilised for endorsement of the predictive model.

Materials and Mix Design

The materials and mix design utilised in the production of CO_2 Concrete for the verification of the predictive models complies with those of the previous mixtures used in the generation of the model in terms of ratio. The mix design for verification is in Table 3.

Declarations

Author Contributions

Vivian W. Y. Tam, Anthony Butera, Khoa N. Le, Luis C. F. Da Silva and Ana. C. J. Evangelista contributed equally to this paper.

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Tables

Table 1

Correlation of artificial neural network predictions of recycled concrete after training

Recycled Aggregate Concrete		Recycled Rubber Concrete		Recycled Glass Concrete	
References	**R^2**	**References**	**R^2**	**References**	**R^2**
Dantas, et al. [1]	0.9710	Hadzima-Nyarko, et al. [49]	0.9779	Ghorbani, et al. [30]	0.9900
Deshpande, et al. [16]	0.9500	Gupta, et al. [50]	0.9924	Ray, et al. [43]	0.9763
Duan, et al. [20]	0.9914	Dat, et al. [29]	0.9770		
Duan, et al. [51]	0.9955	Jalal, et al. [28]	0.9822		
Khademi, et al. [52]	0.9185				

Table 2

Concrete Variables and Mix Design

Variables	Values			
Primary variables				
Water-to-cement ratio (w/c)	0.4	0.45	0.5	
Mixed recycled aggregate replacement (%)	0	30	50	100
Carbonation pressure (kPa)	0	25	75	200
Carbonation duration (min)	0	30	60	120

Mix code	Water-to-cement ratio	Recycled aggregate replacement (%)	Carbon-conditioning duration (min)	Carbon-conditioning pressure (kPa)
Mix code: water-to-cement ratio/recycled aggregate replacement-carbonation duration-carbonation pressure				
0.4/0-0-0	0.4	0	0	0
0.4/30-0-0	0.4	30	0	0
0.4/50-0-0	0.4	50	0	0
0.4/100-0-0	0.4	100	0	0
0.4/30-30-75	0.4	30	30	75
0.4/30-30-200	0.4	30	30	200
0.4/50-30-75	0.4	50	30	75
0.4/100-30-25	0.4	100	30	25
0.4/100-30-75	0.4	100	30	75
0.4/100-30-200	0.4	100	30	200
0.4/30-60-75	0.4	30	60	75
0.4/30-60-200	0.4	30	60	200
0.4/50-60-75	0.4	50	60	75
0.4/100-60-25	0.4	100	60	25
0.4/100-60-75	0.4	100	60	75
0.4/100-60-200	0.4	100	60	200
0.4/30-120-75	0.4	30	120	75

0.4/30-120-200	0.4	30	120	200
0.4/50-120-75	0.4	50	120	75
0.4/100-120-25	0.4	100	120	25
0.4/100-120-75	0.4	100	120	75
0.4/100-120-200	0.4	100	120	200
0.45/0-0-0	0.45	0	0	0
0.45/30-0-0	0.45	30	0	0
0.45/50-0-0	0.45	50	0	0
0.45/100-0-0	0.45	100	0	0
0.45/30-30-75	0.45	30	30	75
0.45/30-30-200	0.45	30	30	200
0.45/50-30-75	0.45	50	30	75
0.45/100-30-75	0.45	100	30	75
0.45/100-30-200	0.45	100	30	200
0.45/30-60-75	0.45	30	60	75
0.45/30-60-200	0.45	30	60	200
0.45/50-60-75	0.45	50	60	75
0.45/100-60-75	0.45	100	60	75
0.45/100-60-200	0.45	100	60	200
0.45/30-120-75	0.45	30	120	75
0.45/30-120-200	0.45	30	120	200
0.45/50-120-75	0.45	50	120	75
0.45/100-120-75	0.45	100	120	75

0.45/100-120-200	0.45	100	120	200
0.5/0-0-0	0.5	0	0	0
0.5/30-0-0	0.5	30	0	0
0.5/50-0-0	0.5	50	0	0
0.5/100-0-0	0.5	100	0	0
0.5/30-30-25	0.5	30	30	25
0.5/30-30-75	0.5	30	30	75
0.5/30-30-200	0.5	30	30	200
0.5/50-30-75	0.5	50	30	75
0.5/100-30-25	0.5	100	30	25
0.5/30-60-25	0.5	30	60	25
0.5/30-60-75	0.5	30	60	75
0.5/30-60-200	0.5	30	60	200
0.5/50-60-75	0.5	50	60	75
0.5/100-60-25	0.5	100	60	25
0.5/30-120-25	0.5	30	120	25
0.5/30-120-75	0.5	30	120	75
0.5/30-120-200	0.5	30	120	200
0.5/50-120-75	0.5	50	120	75
0.5/100-120-25	0.5	100	120	25
0.5/100-120-200	0.5	100	120	200

Recycled aggregate replacement ratio	Cement (kg/m^3)	Water (kg/m^3)	Water-to-cement ratio	Sand (kg/m^3)	10 mm virgin aggregate (kg/m^3)	20 mm virgin aggregate (kg/m^3)	10 mm recycled aggregate (kg/m^3)	20 mm recycled aggregate (kg/m^3)
0.4 w/c								
0%	525.00	210.00	0.4	632.70	344.10	688.20	-	-
30%	525.00	210.00	0.4	632.70	240.87	481.74	103.23	206.46

50%	525.00	210.00	0.4	632.70	172.05	344.10	172.05	344.10
100%	525.00	210.00	0.4	632.70	-	-	344.10	688.20
0.45 w/c								
0%	472.50	210.00	0.45	688.05	343.15	686.30	-	-
30%	472.50	210.00	0.45	688.05	240.21	480.41	102.95	205.89
50%	472.50	210.00	0.45	688.05	171.58	343.15	171.58	343.15
100%	472.50	210.00	0.45	688.05	-	-	343.15	686.30
0.5 w/c								
0%	420.00	210.00	0.5	743.40	342.20	684.40	-	-
30%	420.00	210.00	0.5	743.40	239.54	479.08	102.66	205.32
50%	420.00	210.00	0.5	743.40	171.10	342.20	171.10	342.20
100%	420.00	210.00	0.5	743.40	-	-	342.20	684.40

Table 3

Validation Concrete Variables and Mix Design

Variable	Values		
Water-to-cement ratio (w/c)	0.4	0.45	0.5
Mixed recycled aggregate replacement (%)	40	50	70
Carbonation pressure (kPa)	Ranging from 100 to 200		
Carbonation duration (min)	Ranging from 50 to 120		

Mix Code	Water-to-cement ratio	Recycled aggregate replacement (%)	Carbon-conditioning duration (min)	Carbon-conditioning pressure (kPa)
Mix code: Water-to-cement ratio/recycled aggregate replacement carbonation duration-carbonation pressure				
Water-to-cement ratio of 0.4				
0.4/70-50-130	0.4	70	50	130
0.4/40-110-155	0.4	40	110	155
0.4/40-90-120	0.4	40	90	120
0.4/40-105-150	0.4	40	105	150
0.4/40-65-125	0.4	40	65	125
0.4/50-105-175	0.4	50	105	175
Water-to-cement ratio of 0.45				
0.45/70-105-135	0.45	70	105	135
0.45/70-80-110	0.45	70	80	110
0.45/70-60-135	0.45	70	60	135
0.45/70-75-200	0.45	70	75	200
0.45/40-50-130	0.45	40	50	130
0.45/40-65-145	0.45	40	65	145
0.45/40-95-110	0.45	40	95	110
0.45/40-90-100	0.45	40	90	100
0.45/50-90-115	0.45	50	90	115

Water-to-cement ratio of 0.5				
0.5/70-70-175	0.5	70	70	175
0.5/70-110-145	0.5	70	110	145
0.5/70-120-170	0.5	70	120	170
0.5/70-100-180	0.5	70	100	180
0.5/40-115-165	0.5	40	115	165
0.5/40-75-145	0.5	40	75	145
0.5/40-80-170	0.5	40	80	170

Recycled Aggregate Replacement Percentage	Cement (Kg/m^3)	Water (kg/m^3)	Water-to-Cement Ratio	Sand (kg/m^3)	10 mm Virgin Aggregate (kg/m^3)	20 mm Virgin Aggregate (kg/m^3)	10 mm Recycled Aggregate (kg/m^3)	20 mm Recycled Aggregate (kg/m^3)
Water-to-cement ratio of 0.4								
40%	525.00	210.00	0.4	632.70	206.46	412.92	137.64	275.28
50%	525.00	210.00	0.4	632.70	172.05	344.10	172.05	344.10
70%	525.00	210.00	0.4	632.70	103.23	206.46	240.87	481.74
Water-to-cement ratio of 0.45								
40%	472.50	210.00	0.45	688.05	205.89	411.78	137.26	274.52
50%	472.50	210.00	0.45	688.05	171.58	343.15	171.58	343.15
70%	472.50	210.00	0.45	688.05	102.95	205.89	240.21	480.41
Water-to-cement ratio of 0.5								
40%	420.00	210.00	0.5	743.40	205.32	410.64	136.88	273.76
70%	420.00	210.00	0.5	743.40	102.66	205.32	239.54	479.08

Table 4

Validation Compressive Strength Results and Statistical Results

Standard deviations of multiple regression, artificial neural networks and laboratory data			
Statistic	**Multiple Regression**	**Artificial Neural Network**	**Laboratory Data**
Maximum Value	41.78	40.64	43.19
Minimum Value	25.08	24.50	24.22
Average Value	34.93	34.87	34.93
Standard Deviation	4.73	4.81	5.04

Error and R value for multiple regression and artificial neural networks relative to laboratory results		
Statistic	**Multiple Regression**	**Artificial Neural Network**
Mean Absolute Error	1.30	0.75
Minimum Absolute Error	0.00	0.02
Maximum Absolute Error	3.74	3.22
Mean Square Error	2.90	1.19
Root Mean Square Error	1.70	1.09
Mean Absolute Percentage Error	4.01	2.33
Multiple R	0.94	0.98
R Square	0.88	0.95

Mix Code	**Compressive Strength (MPa)**	**Prediction Error (MPa)**	**Percentage Error (%)**
0.4/70-50-130	42.78	2.44	5.70
0.4/40-110-155	41.31	1.20	2.91
0.4/40-90-120	38.73	1.22	3.15
0.4/40-105-150	42.60	2.46	5.77
0.4/40-65-125	38.81	1.16	3.00
0.4/50-105-175	41.83	1.53	3.65
0.45/70-105-135	38.33	3.03	7.91
0.45/70-80-110	33.16	2.30	6.93
0.45/70-60-135	36.53	1.00	2.74
0.45/70-75-200	35.09	0.45	1.29
0.45/40-50-130	37.25	0.53	1.42
0.45/40-65-145	37.36	0.61	1.63
0.45/40-95-110	36.34	0.33	0.91
0.45/40-90-100	37.55	0.90	2.39
0.45/50-90-115	33.15	3.32	10.00

0.5/70-70-175	29.23	0.61	2.08
0.5/70-110-145	28.48	0.12	0.42
0.5/70-120-170	28.02	0.59	2.09
0.5/70-100-180	27.17	1.07	3.94
0.5/40-115-165	31.68	0.63	1.98
0.5/40-75-145	32.41	0.98	3.02
0.5/40-80-170	30.38	0.79	2.61
	Average	1.24	3.43

Figures

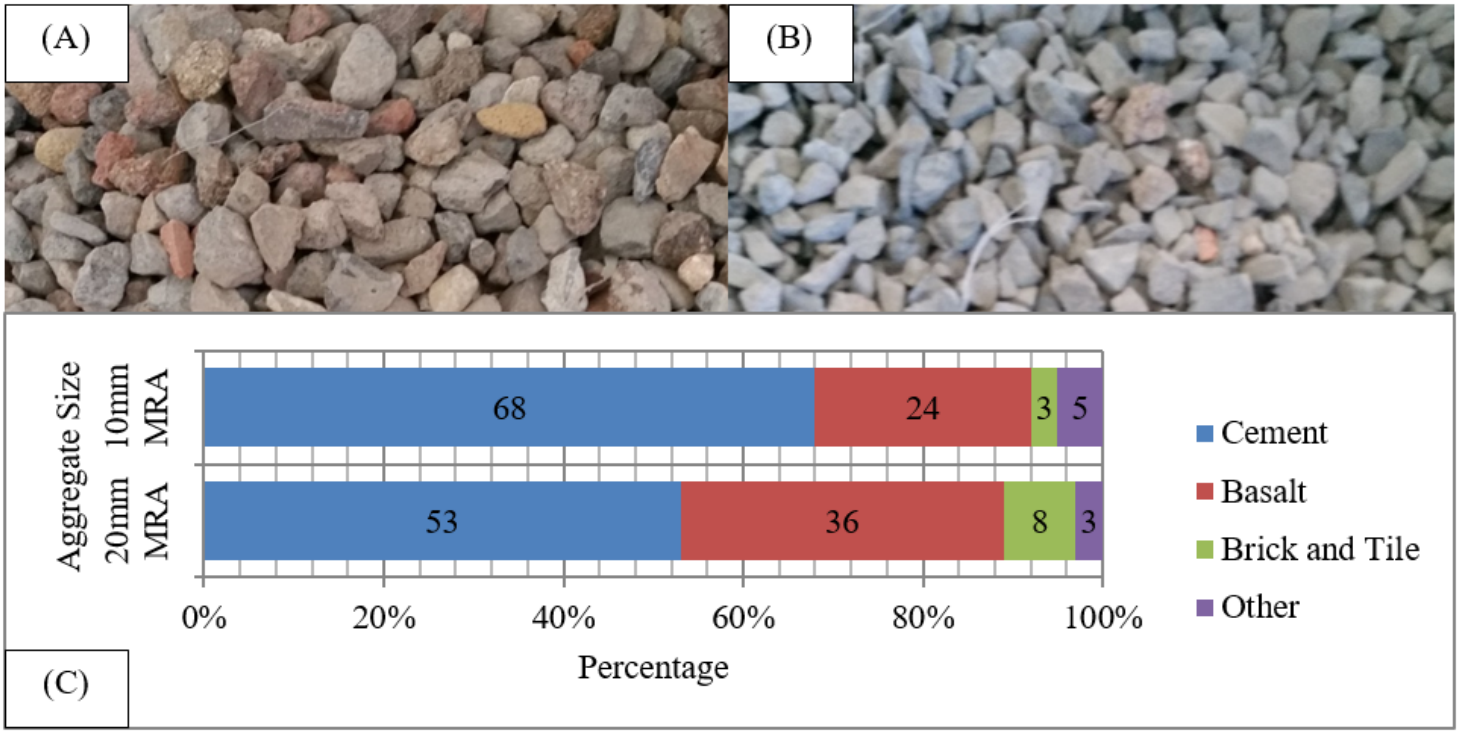

Figure 1

Recycled Aggregate (A), Virgin Aggregate (B) and Recycled Aggregate Classification (C).

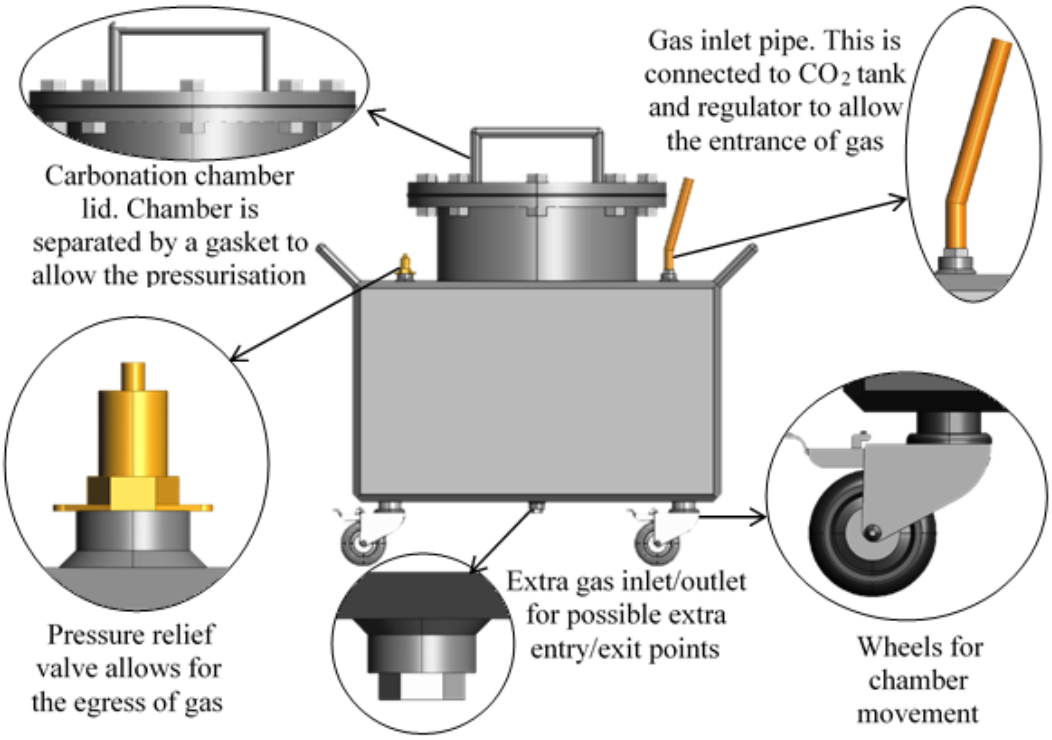

Figure 2

Carbonation Chamber

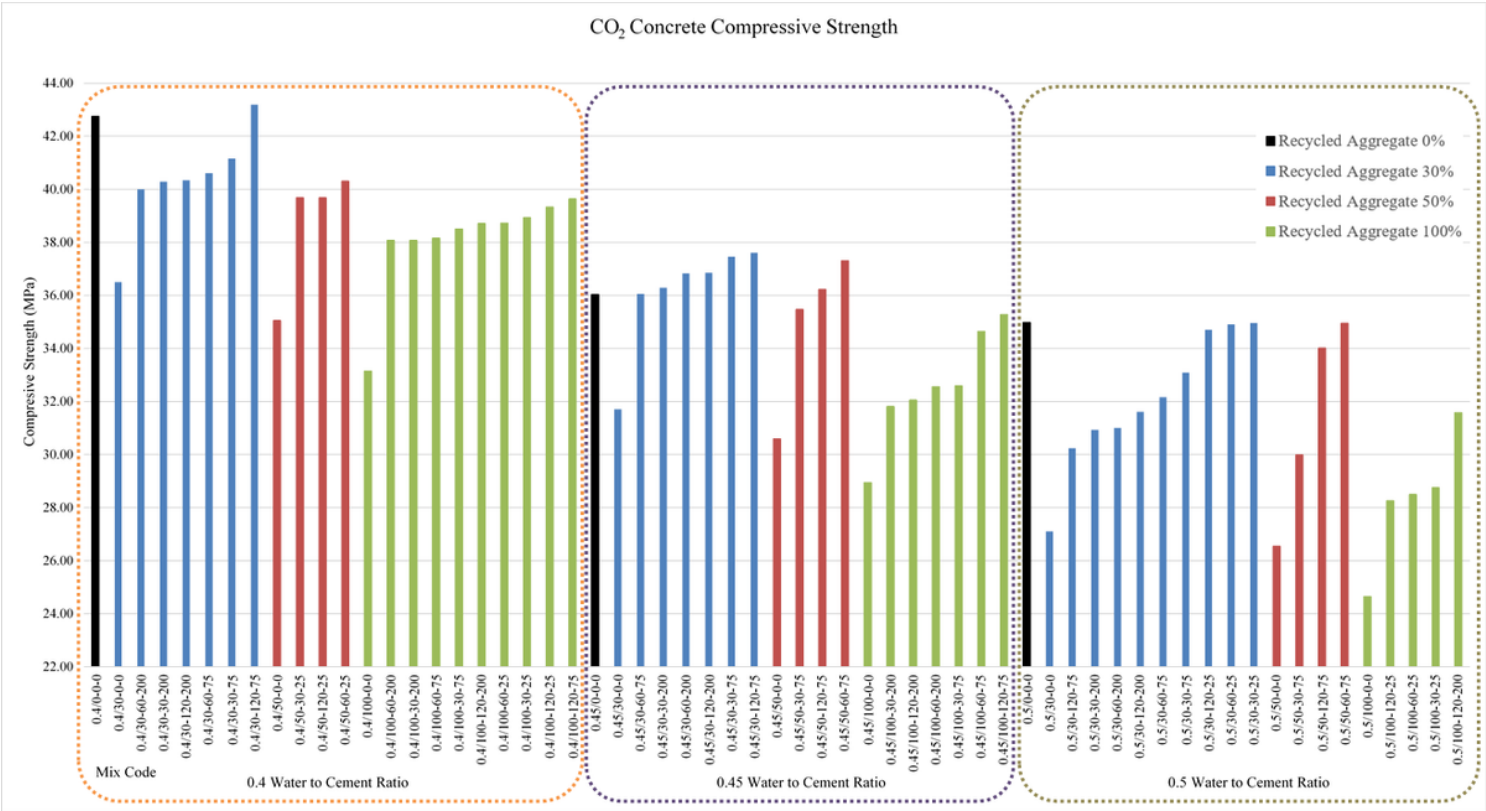

Figure 3

CO2 Concrete laboratory compressive results (creation dataset) (Tam et al., 2021) [6]

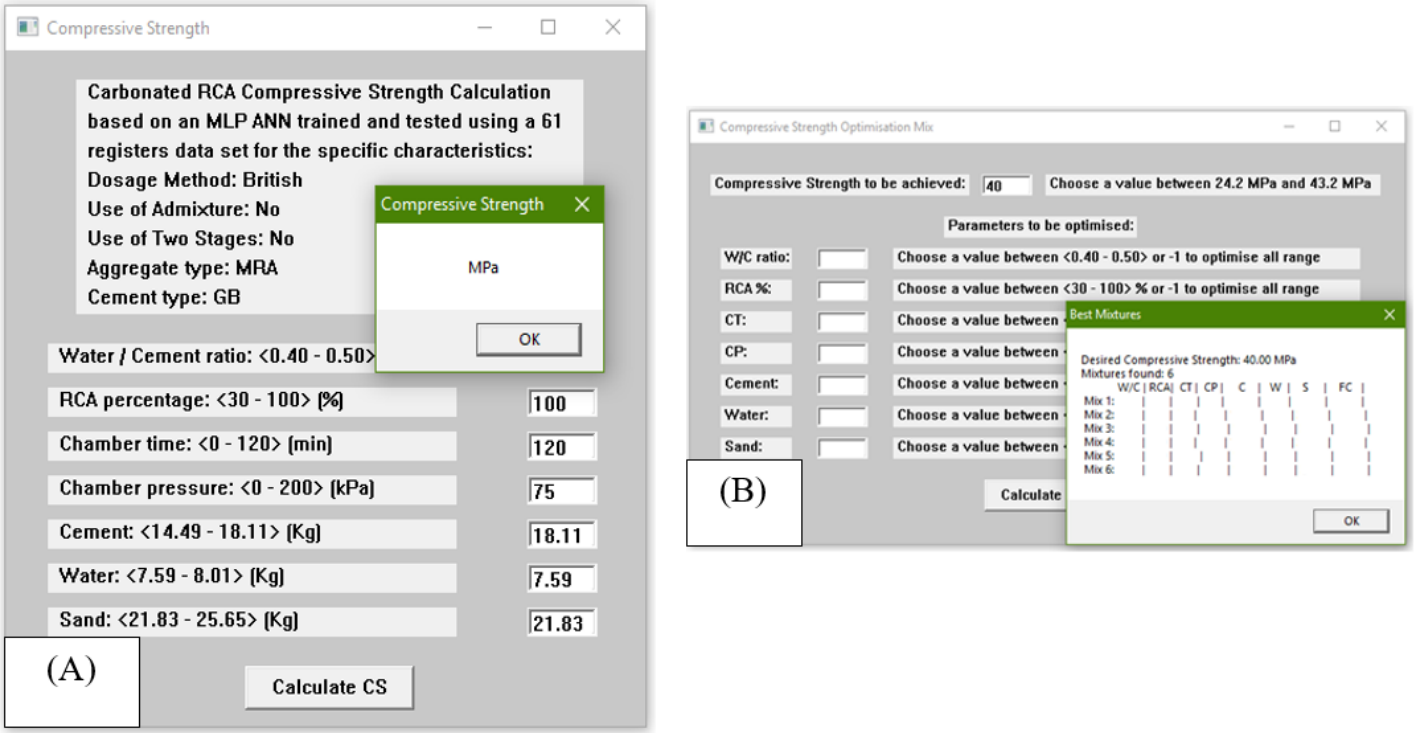

Figure 4

Artificial neural networks for prediction of: (A) CO2 Concrete's compressive strength based on concrete variables; and (B) prediction of concrete mixed designed based on desired CO2 Concrete's compressive strength