# Case-Based Reasoning Approach to Estimating the Strength of Sustainable Concrete

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**Abstract.** Continuing from previous studies of sustainable concrete containing environmentally friendly materials and existing modeling approach to predicting concrete properties, this study developed an estimation methodology to predicting the strength of sustainable concrete using an advanced case-based reasoning approach. It was conducted in two steps: (i) establishment of a case database and (ii) development of an advanced case-based reasoning model. Through the experimental studies, a total of 144 observations for concrete compressive strength and tensile strength were established to develop the estimation model. As a result, the prediction accuracy of the A-CBR model (i.e., 95.214% for compressive strength and 92.448% for tensile strength) performed superior to other conventional methodologies (e.g., basic case-based reasoning and artificial neural network models). The developed methodology provides an alternative approach in predicting concrete properties and could be further extended to the future research area in durability of sustainable concrete.

**Keywords:** Sustainable concrete; Advanced case-based reasoning; Environmentally friendly concrete materials; Concrete mixture design; Concrete strength prediction; Optimization process

## 1. Introduction

The eco-friendly sustainable concrete, as defined by Valipour et al. (2017), is produced through using natural and/or recyclable materials with less environmental destruction associated with improved sustainability in performance, environmental and economic aspects. The sustainability movement in the construction industry and the shortage of natural resources have driven the research and practice of green ecological concrete (Xiao et al., 2015). Besides saving natural resources, lower carbon footprint and improved structural and thermal performance are also considered a sustainability in concrete production (Haque et al., 2002; Jin et al., 2015). To achieve the sustainable concrete production, alternative or environmentally friendly materials such as supplementary cementitious materials (SCMs) and recycled aggregate could be added to concrete mixture design in addition to the conventional materials (i.e., virgin aggregate, sand, Portland cement or PC, water, and chemical admixture).

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Both alternative and conventional materials in concrete mixture design could become independent variables that would affect concrete properties. Most previous studies in predicting mechanical properties of concrete (e.g., Hossain and Lachemi, 2006; Saridemir et al., 2009; Topçu and Boğa, 2010; Atici, 2011; Mastali et al., 2016) have not adopted a comprehensive list of mixture-design-based independent variables. Other studies (e.g., Yang et al., 2005; Bondar et al., 2011; Limbachiya et al., 2012), due to limited experimental data, were unable to conduct a quantitative analysis on how the alternative cementitious or aggregate materials would affect the sustainability of concrete, or how to utilize the existing data to optimize the mechanical properties of concrete. To address this concern, a proper list of input parameters, as indicated by Biernacki and Gottapu (2015), need to be statistically significant in the estimation of concrete properties.

Based on the earlier market survey by Jin et al. (2015) that focused on the U.S. sustainable concrete production, Portland limestone cement (PLC), Haydite lightweight aggregate (LWA), and fly ash Class F were adopted as alternative materials, which were used for the concrete mixture design in this study. Incorporating these selected alternatives or waste materials in sustainable concrete mixture design, and extending the earlier relevant study of mixture design for sustainable concrete (i.e., Tapali et al., 2013), this study aimed to apply the newly developed advanced case-based reasoning (A-CBR) approach in concrete strength prediction. The A-CBR can be developed in the following three processes (i.e., calculating the case similarity; improving the prediction accuracy; and optimizing the prediction model). The objectives of this study are: (i) to build the comprehensive case database from a holistic list of mixture-design-based independent input variables; (ii) to establish the A-CBR approach by integrating the CBR, MRA, ANN, SVM, and generic algorithm; (iii) to obtain the prediction results using an A-CBR approach for both compressive and tensile strength of sustainable concrete; and (iv) to compare the prediction accuracy using an A-CBR to other existing approach (i.e., basic CBR, MRA, ANN, and SVM). This study contributes to previous research in concrete sustainability and property analysis by: (i) introducing the alternative A-CBR approach in the concrete property studies starting from strength prediction work based on sustainable concrete mixture; (ii) initiating future research directions in durability of sustainable concrete by using an A-CBR; and (iii) optimizing materials usage in mixture design to achieve maximum targeted performance of concrete containing environmentally friendly materials.

## 2. Background

### *2.1 Sustainability movement in concrete production*

Concrete, as the most widely used construction material worldwide, its production and consumption has raised environmental concerns (Benhelal et al., 2013; Henry and Kato, 2014; Yang et al., 2015). Concrete materials, including PC and natural aggregate, their manufacturing or processing process are either being energy-intensive, emitting greenhouse gas, or causing depletion of natural resources (Langer and Arbogast, 2002; Bentz, 2010; Bondar et al., 2011; Tapali et al., 2013; Shafigh et al., 2016). Researchers have been exploring environmentally friendly concrete materials as partial replacements to traditional PC or aggregate in concrete mixture design, for example, recycled mineral admixture applied in lightweight aggregate concrete studied by Wang et al. (2012), coarse aggregate made of waste streams from oil palm shells joint with high volume fly ash in concrete mixture conducted by Shafigh et al. (2016), and green concrete composites consisting of waste carpet fibres and palm oil fuel ash in the study of Mohammadhosseini et al. (2017b). Studying the engineering properties of sustainable concrete containing environmentally friendly materials has been undergoing continuous movement in recent years, such as the compressive strength and elastic modulus of recycled aggregate concrete studied by Duan and Poon (2014), the compressive strength of hydraulic lime-pozzolan concrete tested by Grist et al. (2015), and mechanical properties of recycled lightweight expanded clay aggregate concrete evaluated by Bogas et al. (2015). Similar studies of sustainable concrete can be found from various other cases (e.g., Guo et al., 2015; Farahani et al., 2017; Mohammadhosseini et al. (2017a).

### *2.2 Existing modeling approach in estimating concrete properties*

Several analytical and modeling approaches to predicting the mechanical properties of concrete (e.g., compressive and tensile strength) have been developed by multiple researchers in the concrete field. These modeling methods can be categorized as multiple regression analysis (Yeh, 1998; Deepa et al., 2010; Kandasamy and Akila, 2015; Mastali et al., 2016), fuzzy logic or FL (Demir, 2005; Saridemir et al., 2009), support vector machine or SVM (Juncai et al., 2015; Abd and Abd, 2017), genetic algorithm (Erdogan and Bakir, 2013), as well as data mining including artificial neural network or ANN (Ni and Wang, 2000; Atici, 2011; Duan and Poon, 2014), as well as decision tree or DT (Chou et al., 2011; Omran et al., 2016). All of these existing methods have their own limitations in predicting the mechanical properties of concrete. For instance, MRA achieves the results through statistical approach. However, the results could be too linear for being applied in a standardized model (Phaobunjong, 2002; Lowe et al., 2006). The application of FL in predicting concrete properties would be complicated as the number of variables increases (Demir, 2005). Yan et al. (2003) reported that SVM could resolve practical problems such as nonlinearity and high-dimensional space. However, its prediction accuracy could decrease when data structures become complicated because it is based on statistical learning theory. ANN, on the other hand, can usually achieve higher accuracy in prediction, but it is a ‘black box’ that could not explain the model structure (Attalla and Hegazy, 2003; Rifat, 2004). Finally, although DT is easy to understand and simple to implement, its prediction accuracy could decrease when independent variables become complicated (Sheng et al., 2000; Müller and Wiederhold, 2002).

### *2.3 Advanced case-based reasoning approach*

An A-CBR has the potential of achieving superior performance in predicting concrete properties compared to the aforementioned existing methods, as indicated by a few recent studies conducted in other fields, such as cost estimation in Dogan et al (2006) and Koo et al. (2011), building energy management in Koo et al. (2014b), natural resource potential in Koo et al. (2013), and infrastructure management in Koo et al. (2014a).

However, there has been limited studies so far in applying an A-CBR approach to the prediction of the mechanical properties of concrete. It has not been well understood whether an A-CBR approach, as the integrated methodology in predicting the mechanical properties of concrete, would outperform other existing methods. Therefore, it still needs to be explored whether an A-CBR approach could serve as an alternative prediction method that can complement the current modeling approach. In addition, for the first time, this study attempted to improve the prediction accuracy by integrating the SVM model as well as the MRA and ANN models used in the previous studies using an A-CBR approach.

## 3. Materials and Methods

### *3.1. Advanced case-based reasoning approach*

#### *3.1.1 Experimental materials*

In this study, PLC type general use cement was selected as the alternative cementitious material. To achieve lower carbon footprint, the PLC was mixed with 12% limestone as calculated by the method in ASTM C150-05. The conventional PC Type I/II was used as the experimental control group. Fly ash Class F was chosen as the SCM to partly substitute PC or PLC by weight for further improvement of concrete sustainability. Table 1 shows the mill test reports provided by suppliers on three types of cementitious materials.

Table 1 Mill test reports of cementitious materials used in this study

| Cementitious material | $SiO_2$ (%) | $Al_2O_3$ (%) | $Fe_2O_3$ (%) | CaO(%) | MgO(%) | $SO_3$ (%) | Alkalis (%) |
|---|---|---|---|---|---|---|---|
| PC | 20.1 | 5.0 | 3.3 | 63.2 | 2.4 | 2.6 | 0.56 |
| PLC | 18.4 | 4.6 | 3.0 | 59.9 | 2.9 | 3.6 | 0.65 |
| Fly ash Class F | 43.7 | 21.0 | 23.8 | 5.0 | 1.0 | 1.7 | 1.97 |

Pea gravel with the maximum size of 10 mm was selected as the natural coarse aggregate (CA) in this study. Haydite LWA at size B, with the similar size as pea gravel, was used as the alternative CA to partly replace pea gravel by volume. Haydite LWA was evaluated as sustainable concrete material according to Jin et al. (2015) and Omran et al. (2016). Brown sand, the locally available natural resource, was chosen as the fine aggregate in the concrete mixture. Table 2 shows the dry densities and fineness modulus of aggregates (e.g., Pea gravel, Haydite LWA at size B, and brown sand).

Table 2 Dry densities and fineness modulus of aggregates used in this study

| Type of aggregate | *Loose bulk dry density($kg/m^3$) | *Oven dry density($kg/m^3$) | Fineness modulus |
|---|---|---|---|
| Pea gravel | 1,600 | 2,643 | 6.01 |
| Haydite LWA at size B | 673 | 1,300 | 5.39 |
| Brown sand | 1,600 | 2,611 | 2.48 |

*The Loose bulk dry density: provided by the supplier; Oven dry density: defined by ASTM C127-04 and ASTM C128-07

Haydite LWA has internal voids with much lower density compared to the pea gravel. To prevent the slump loss of concrete containing Haydite LWA, all Haydite LWA were pre-saturated with water and then drained by strictly following the guideline provided by the supplier. The internally absorbed moisture within Haydite LWA was not included in the calculation of water-to-cementitious material (w/c) ratio. Instead, the absorbed moisture in the internal voids of Haydite LWA could contribute to the cement secondary hydration after concrete initial set through internal curing.

Micro Air®, the air-entraining admixture (AEA), was used in this study to provide air bubbles and increase air content to 6-7% for concrete containing Haydite LWA, as suggested by the Haydite supplier. Air content equal to 6% or 7.5% was suggested by ACI 318-0843 for concrete with a nominal maximum aggregate size of 10 mm and exposed to freezing and thawing.

#### *3.1.2 Experimental design*

The absolute volume method was adopted in this study to design the mixture of concrete following ACI 211.2.44. To study the joint effects of PLC, fly ash Class F, and Haydite LWA on concrete properties, totally 36 batches of concrete mixture were designed as illustrated in Fig.1.

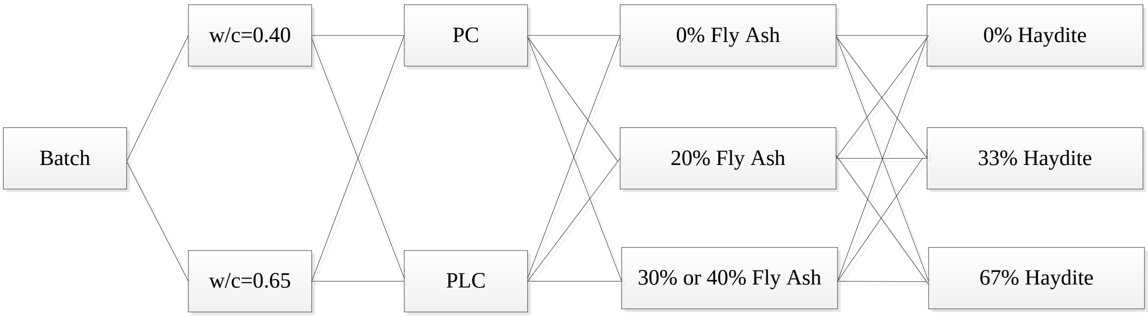


Fig.1 Experimental design of 36 concrete batches

As displayed in Fig.1, two different types of w/c ratios were defined in the experimental trial for both PC and PLC concrete. Fly ash was used to substitute PC or PLC at rates from 0% to as high as 40%. Similarly, Haydite LWA was added to replace pea gravel at substitution rates of 0%, 33%, and 67%. Tasks involved in this experimental study including making, pouring and curing of concrete, as well as strength tests of specimen are listed in Table 3.

Table 3 Tasks involved in the concrete mixing and strength tests

| Tasks | Equipment/tools | Guideline |
|---|---|---|
| Making, pouring and curing concrete | 102 mm X 204 mm (or 4”x8”) single-use cylinder plastic molds, tamping rod | ASTM C31/C31M–06 [34] |
| Compressive strength test | Testing machine (Humboldt) | ASTM C39/C39–05 [35] |
| Tensile strength test (split cylinder) | Testing machine (Humboldt) | ASTM C496 [36] |

All casted cylinders were air-cured at a constant temperature of 23 °C in the laboratory and the compressive and split tensile strength were tested at four different curing ages (i.e., Day 3, Day 7, Day 28, and Day 90).

#### *3.1.3 Design variables in the mixture of concrete*

Continuing from previous studies, including those of Saridemir et al. (2009), Chou et al. (2011), Erdal et al. (2013), and Omran et al. (2016), where the numerical values of materials within concrete mixture design were chosen as independent variables for the prediction of concrete strength, this research adopted a comprehensive list of concrete materials plus the concrete curing age as independent variables. All the nine independent variables are listed in Table 4.

Table 4 Factors affecting the concrete compressive strength and tensile strength

| Variables | Attributes | | Units |
|---|---|---|---|
| Indepen-dent variable | Concrete age | $X_1$ | ( ) days |
| | Water | $X_2$ | ( ) kg/m$^3$ |
| | Portland cement | $X_3$ | ( ) kg/m$^3$ |
| | Portland limestone cement | $X_4$ | ( ) kg/m$^3$ |
| | Fly ash | $X_5$ | ( ) kg/m$^3$ |
| | Sand | $X_6$ | ( ) kg/m$^3$ |
| | Coarse aggregate | $X_7$ | ( ) kg/m$^3$ |
| | Haydite Lightweight aggregate | $X_8$ | ( ) kg/m$^3$ |
| | Air entraining-admixture | $X_9$ | ( ) ml/m$^3$ |
| Depend-ent variable | Compressive strength | $Y_1$ | ( ) Mpa |
| | Tensile strength | $Y_2$ | ( ) Mpa |

Except the curing age, which was measured by days, all other independent variables listed in Table 4 were based on the amount of each material consumed per m$^3$ of concrete produced. For example, the unit of Haydite LWA is based on the weight of Haydite of (kg/m$^3$) used in concrete mixture design, and AEA is measured by the amount of air entrainment measured in millilitre.

### *3.2 Development of an advanced case-based reasoning model*

This study attempted to apply the newly developed A-CBR approach in predicting the compressive and tensile strength of sustainable concrete. The A-CBR model could not only be superior to the existing methodologies (e.g., ANN and SVM) in terms of prediction accuracy, but also provide the retrieved historical-cases as references, which is the advantage of the basic CBR model displayed in studies from Koo et al. (2011); Koo et al. (2013); Koo et al. (2014a) and Koo et al. (2014b). The A-CBR model can be developed in three steps: (i) Step 1: selecting the similar cases; (ii) Step 2: filtering the selected cases; and (iii) Step 3: improving the prediction accuracy.

### *3.2.1 Step 1: Selecting the similar cases*

As the first step of the basic CBR approach, the case similarity should be calculated by summing up the weighted attribute similarity, which can be expressed with the basic matrix operation (refer to Eq. (1)).

$$\begin{pmatrix} f_{AS_{11}} & \cdots & f_{AS_{1n}} \\ \vdots & \cdot & \vdots \\ f_{AS_{m1}} & \cdots & f_{AS_{mn}} \end{pmatrix} \begin{pmatrix} f_{AW_1} \\ \vdots \\ f_{AW_n} \end{pmatrix} = \begin{pmatrix} f_{CS} \\ \vdots \\ f_{CS_m} \end{pmatrix} \quad \text{Eq. (1)}$$

where, $f_{AS}$ stands for the function for calculating the attribute similarity; $f_{AW}$ stands for the function for calculating the attribute weight; $f_{CS}$ stands for the function for calculating the case similarity; m stands for the number of cases; and n stands for the number of attributes.

For the consistency of the attribute weight in the basic CBR model, the actual values of independent and dependent variables should be converted to the standardized values within the range of 0 to 1 (refer to Eq. (2)).

$$SV = \left| \frac{AV - AV^{\min}}{AV^{\max} - AV^{\min}} \right| \quad \text{Eq. (2)}$$

where, SV stands for the standardized value for the actual value (AV) (which is dimensionless); AVmin stands for the minimum value of the AV; and AVmax stands for the maximum value of the AV.

Similar cases can be retrieved based on the case similarity, which can be determined using attribute similarity and attribute weight (refer to Eq. (3)). First, if the scale of a given attribute is defined as a continuous scale, the attribute similarity can be calculated using Eq. (4). If the attribute similarity is determined to be higher than the minimum criterion for scoring the attribute similarity (MCAS), it can be valid; otherwise, it should be set at zero. In this way, as the MCAS has an effect on the attribute similarity, the case similarity, and the prediction accuracy of the basic CBR model, it should be determined through the optimization process using a genetic algorithm (GA). Thus, the MCAS was determined to be set as adjustable parameter in the optimization process. For example, in the case of the air entraining-admixture (one of the design variables in Table 4), the attribute similarity between the case No.127 (137 ml/m3) and the case No.120 (148 ml/m3) can be determined at 91.97% (refer to Eq. (4)). As shown in Section 4.1.2, if the MCAS of the air entraining-admixture would be set at 33.09% through the optimization process (refer to Table 6), the attribute similarity score can be accepted. Conversely, if the MCAS would be set at more than 91.97% (e.g., 92%), the attribute similarity score could be set at zero.

Second, as the attribute weight can not only affect the case similarity, but also the prediction accuracy of the basic CBR model, it should be determined via the optimization process using a GA. Thus, the range of the attribute weight (RAW) was determined to be set as adjustable parameter in the optimization process. For example, the procedure for calculating the case similarity between the case No.127 and the case No.120 is as follows. As shown in Section 4.1.2, if the RAW of the air entraining-admixture would be set at 1.53% through the optimization process (refer to Table 6), the weighted attribute similarity can be determined at 1.407% (= 91.97% of attribute similarity × 1.53% of attribute weight) (refer to Eq. (3)). Similarly, all of the weighted attribute similarity can be calculated. Finally, the case similarity between the case No.127 and the case No.120 can be determined at 91.39% (refer to Table 9).

$$f_{CS_m} = \frac{\sum_{i=1}^{n} \left( f_{AW_{mi}} \times f_{AS_{mi}} \right)}{\sum_{i=1}^{n} \left( f_{AW_{mi}} \right)} \quad \text{Eq. (3)}$$

$$f_{AS_n} = \begin{cases} 100 - \left( \dfrac{\left| SV_{TC} - SV_{RC} \right|}{SV_{TC}} \times 100 \right) & if \quad f_{AS_n} \geq f_{MCAS} \\ 0 & if \quad f_{AS_n} < f_{MCAS} \end{cases} \quad \text{Eq. (4)}$$

where, $f_{CS}$ stands for the function for calculating the case similarity; $f_{AW}$ stands for the function for calculating the attribute weight; $f_{AS}$ stands for the function for calculating the attribute similarity; m stands for the number of cases; n stands for the number of attributes; $SV_{TC}$ stands for the standardized value of a certain attribute in a test case; $SV_{RC}$ stands for the standardized value of a certain attribute in a retrieved case; and $f_{MCAS}$ stands for the function for calculating the *MCAS*.

### *3.2.2 Step 2: Filtering the selected cases*

For improving the prediction accuracy of the basic CBR model established in Section 3.2.1, the selected cases should be thoroughly reviewed once again with the filtering engine, which can be developed by integrating the predicted values from the MRA, ANN, and SVM models. As the first attempt, this study investigates how the SVM model affects the improvement of the prediction accuracy in an A-CBR approach. First, based on the predicted values by model, the mean absolute percentage error (MAPE) and prediction accuracy by model (i.e., MRA, ANN, and SVM) can be calculated using Equations (5) and (6), respectively.

$$f_{MAPE} = \left( \sum_{i=1}^{m} \left| \frac{SV_i - PV}{SV_i} \right| \right) \times \frac{1}{m} \times 100 \qquad \text{Eq. (5)}$$

$$f_{PA} = 100 - f_{MAPE} \qquad \text{Eq. (6)}$$

where, $f_{MAPE}$ stands for the function for calculating the MAPE; SV stands for the standardized value of dependent variable; PV stands for the predicted value of dependent variable; m stands for the number of cases; and $f_{PA}$ stands for the function for calculating the prediction accuracy.

Second, using the MAPE by a model (i.e., MRA, ANN, and SVM), the predicted range for a given model (i.e., PRMRA, PRANN, and PRSVM) can be established (refer to Eqs. (7) - (9)). Thereafter, the filtering engine can be determined by considering the predicted ranges of models (refer to Eqs. (10) - (15)). That is, the predicted ranges of models can be used to determine the cross-range between the predicted values of the models (e.g., the cross-range between the predicted values of the SVM and ANN models (CRSA), refer to Eq. (14)). In addition, the tolerance range of CRSA (TRCRSA) can be used to find the filtering engine (refer to Eq. (15)). In this way, as the TRCRSA can affect the filtering engine that is closely related to the prediction accuracy of the basic CBR model, it should be determined via the optimization process using a GA. Thus, the TRCRSA was determined to be set as adjustable parameter in the optimization process.

$$PV_{MRA} \times \left(1 - \frac{MAPE_{MRA}}{100}\right) \le PR_{MRA} \le PV_{MRA} \times \left(1 + \frac{MAPE_{MRA}}{100}\right) \qquad \text{Eq. (7)}$$

$$PV_{ANN} \times \left(1 - \frac{MAPE_{ANN}}{100}\right) \le PR_{ANN} \le PV_{ANN} \times \left(1 + \frac{MAPE_{ANN}}{100}\right) \qquad \text{Eq. (8)}$$

$$PV_{SVM} \times \left(1 - \frac{MAPE_{SVM}}{100}\right) \le PR_{SVM} \le PV_{SVM} \times \left(1 + \frac{MAPE_{SVM}}{100}\right) \qquad \text{Eq. (9)}$$

where, $PR_{MRA}$ stands for the predicted range of the MRA model; $PV_{MRA}$ stands for the predicted value of the MRA model; $MAPE_{MRA}$ stands for the MAPE of the MRA model; $PR_{ANN}$ stands for the predicted range of the ANN model; $PV_{ANN}$ stands for the predicted value of the ANN model; $MAPE_{ANN}$ stands for the MAPE of the ANN model; $PR_{SVM}$ stands for the predicted range of the SVM model; $PV_{SVM}$ stands for the predicted value of the SVM model; and $MAPE_{SVM}$ stands for the MAPE of the SVM model.

$$Max(Min(PR_{MRA}), Min(PR_{ANN})) \le CRMA \le Min(Max(PR_{MRA}), Max(PR_{ANN})) \qquad \text{Eq. (10)}$$

$$Min(CRMA) \times \left(1 - \frac{TRCRMA}{100}\right) \le CRMA^{*} \le Max(CRMA) \times \left(1 + \frac{TRCRMA}{100}\right) \qquad \text{Eq. (11)}$$

$$Max(Min(PR_{MRA}), Min(PR_{SVM})) \le CRMS \le Min(Max(PR_{MRA}), Max(PR_{SVM})) \qquad \text{Eq. (12)}$$

$$Min(CRMS) \times \left(1 - \frac{TRCRMS}{100}\right) \le CRMS^{*} \le Max(CRMS) \times \left(1 + \frac{TRCRMS}{100}\right) \qquad \text{Eq. (13)}$$

$$Max(Min(PR_{SVM}), Min(PR_{ANN})) \le CRSA \le Min(Max(PR_{SVM}), Max(PR_{ANN})) \qquad \text{Eq. (14)}$$

$$Min(CRSA) \times \left(1 - \frac{TRCRSA}{100}\right) \le CRSA^{*} \le Max(CRSA) \times \left(1 + \frac{TRCRSA}{100}\right) \qquad \text{Eq. (15)}$$

where, *CRMA* stands for the cross-range between the predicted values of the MRA and ANN models; *TRCRMA* stands for the tolerance range of CRMA; *CRMA** stands for the filtering range in which TRCRMA is applied to CRMA; *CRMS* stands for the cross-range between the predicted values of the MRA and SVM models; *TRCRMS* stands for the tolerance range of CRMS; *CRMS** stands for the filtering range in which TRCRMS is applied to CRMS; *CRSA* stands for the cross-range between the predicted values of the SVM and ANN models; *TRCRSA* stands for the tolerance range of CRSA; and *CRSA** stands for the filtering range in which TRCRSA is applied to CRSA.

For example, the procedure for calculating the $CRSA^*$ for the case No.127 is as follows.

- First, using the ANN model, the predicted compressive strength of the case No.127 ($PV_{ANN}$) would be determined at 58.085. The MAPE of the ANN model ($MAPE_{ANN}$) would be determined at 4.02% (refer to Table 5). Thus, the predicted range of the ANN model ($PR_{ANN}$) would be determined within the range of 55.753 (= 58.085 × (1-0.0402)) to 60.417 (= 58.085 × (1+0.0402)) (refer to Equation (8)).
- Second, using the SVM model, the predicted compressive strength of the case No.127 ($PV_{SVM}$) would be determined at 59.645. The MAPE of the SVM model ($MAPE_{SVM}$) would be determined at 6.89% (refer to Table 5). Thus, the predicted range of the SVM model ($PR_{SVM}$) would be determined within the range of 55.534 (= 59.645 × (1-0.0689)) to 63.756 (= 59.645 × (1+0.0689)) (refer to Equation (9)).
- Third, based on the predicted range of the ANN model ($PR_{ANN}$) and the predicted range of the SVM model ($PR_{SVM}$), the *CRSA* would be determined within the range of 55.753(= Max (55.534, 55.753)) to 60.417(= Min (63.756, 60.417)) (refer to Equation (14)).
- Fourth, the TRCRSA would be set at 6.25% through the optimization process (refer to Table 6); and thus, *CRSA** would be determined within the range of52.268 (= 55.753 × (1-0.0625)) to 64.193 (= 60.417 × (1+0.0625)) (refer to Equation (15)).

### *3.2.3 Step 2: Filtering the selected cases*

In developing the A-CBR model, various adjustable parameters should be established in the optimization process so that the prediction accuracy of the A-CBR model can be improved. As mentioned in the previous Sections, this study established three kinds of adjustable parameters in the optimization process: (i) MCAS; (ii) RAW; and (iii) TRCRMA/TRCRMS/TRCRSA. The first two parameters should be considered in calculating the case similarity (refer to Equations (3) and (4)), and the third parameter should be considered in establishing the filtering engine (refer to Equations (7) - (15)). Furthermore, since the basic CBR model provides the predicted results with the retrieved historical-cases as references, the number of retrieved cases should be determined in the optimization process. Thus, the range of case selection (RCS) was also determined to be set as adjustable parameter in the optimization process. As a result, a total of four adjustable parameters were set in the optimization process using a GA. The GA, a representative search algorithm, is generally used to find the optimal solution from a number of possible combinations of the adjustable parameters. The software program *'Evolver'* was adopted to develop the optimization process.

- Adjustable parameter (i) – *MCAS*: To calculate the attribute similarity, MCAS was set as adjustable parameter within the range of 0-100% in a GA (refer to Section 3.2.1).
- Adjustable parameter (ii) – *RAW*: To determine the attribute weight, RAW was set as adjustable parameter within the range of 0-100% in a GA (refer to Section 3.2.1).
- Adjustable parameter (iii) – *TRCRMA/TRCRMS/TRCRSA*: To determine the filtering engine, TRCRMA/TRCRMS/TRCRSA were set as adjustable parameter within the range of 0-100% in a GA (refer to Section 3.2.2).
- Adjustable parameter (iv) – *RCS*: To determine the number of retrieved cases, RCS was set as adjustable parameter within the range of 0-100% in a GA (refer to Section 3.2.3).

## 4. Results and Discussion

This study developed an A-CBR modeling approach to estimating the compressive and tensile strength of sustainable concrete. First, the feasibility of the developed A-CBR model was validated. Next, a case study was conducted to illustrate the detailed estimation process for the strength of sustainable concrete using the developed A-CBR model, in which the case No.127 was used.

### *4.1 Validation of the feasibility of the developed A-CBR model*

#### *4.1.1 A comparison of the prediction accuracy by estimation model*

To validate the prediction accuracy of the A-CBR model, it was compared with those of other methodologies often used in the previous studies (i.e., the basic CBR, MRA, ANN, and SVM models).

Table 5 shows the comparison of the prediction accuracy and standard deviation by estimation model.

- For compressive strength: The prediction accuracy and standard deviation of the A-CBR (SVM&ANN) model were superior to those of other A-CBR models (i.e., A-CBR (MRA&ANN) and A-CBR (MRA&SVM) models). Namely, the prediction accuracy and standard deviation of the A-CBR (SVM&ANN) model were determined to be the best (95.214% and 3.059%, 1st), followed by those of the A-CBR (MRA&ANN) model (94.531% and 3.078%, ranked 2nd) and the A-CBR (MRA&SVM) model (93.623% and 6.513%, ranked 3rd). Furthermore, the prediction accuracy and standard deviation of the A-CBR (SVM&ANN) model were superior to those of other conventional approaches (i.e., the basic CBR, MRA, ANN, and SVM). Even if the prediction accuracy of the A-CBR (SVM&ANN) model appeared to be a little bit lower than that of the ANN model, its prediction accuracy was good enough to accurately estimate the compressive strength. Furthermore, the difference between these two models was extremely small.

Table 5 Comparison of the prediction accuracy and standard deviation by estimation model

| Classification | Type of estimation model | Prediction accuracy | Standard deviation |
|---|---|---|---|
| Compressive Strength | Basic *CBR model | 79.029 | 9.581 |
| | *MRA model | 88.338 | 8.331 |
| | *ANN model | 95.985 | 4.056 |
| | *SVM model | 93.107 | 7.300 |
| | *A-CBR model (MRA&ANN) | 94.531 | 3.078 |
| | A-CBR model (MRA&SVM) | 93.623 | 6.513 |
| | A-CBR model (SVM &ANN) | 95.214 | 3.059 |
| Tensile Strength | Basic CBR model | 83.211 | 11.565 |
| | MRA model | 87.187 | 10.805 |
| | ANN model | 91.384 | 6.602 |
| | SVM model | 87.443 | 10.509 |
| | A-CBR model (MRA&ANN) | 91.427 | 4.667 |
| | A-CBR model (MRA&SVM) | 90.763 | 6.408 |
| | A-CBR model (SVM &ANN) | 92.448 | 6.083 |

*CBR: the case-based reasoning; MRA: the multiple regression analysis; SVM: the support vector machine; ANN: the artificial neural network; A-CBR: the advanced case-based reasoning.

- For tensile strength: The prediction accuracy and standard deviation of the A-CBR (SVM&ANN) model were superior to those of other A-CBR models (i.e., A-CBR (MRA&ANN) and A-CBR (MRA&SVM) models). Namely, the prediction accuracy and standard deviation of the A-CBR (SVM&ANN) model were determined to be the best (92.448% and 6.083%, 1st), followed by those of the A-CBR (MRA&ANN) model (91.427% and 4.667%, ranked 2nd) and the A-CBR (MRA&SVM) model (90.763% and 6.408%, ranked 3rd). Furthermore, the prediction accuracy and standard deviation of the A-CBR (SVM&ANN) model were superior to those of other conventional approaches (i.e., the basic CBR, MRA, ANN, and SVM).

In conclusion, it was determined that the A-CBR model can be properly used for retrieving similar cases from the case database. Consequently, the cases retrieved by the A-CBR model can be used to estimate the compressive and tensile strength of sustainable concrete in the early construction phase. Meanwhile, the A-CBR (SVM&ANN) model was proven to be superior to other A-CBR models (i.e., A-CBR (MRA&ANN) and A-CBR (MRA&SVM) models. It indicates that the higher prediction accuracy of the A-CBR model could be expected if more accurate models (i.e., ANN and SVM) were used to develop the filtering engine in the A-CBR model.

#### *4.1.2 Optimized values of the adjustable parameters*

As mentioned in Section 4.1.1, the prediction accuracy of the A-CBR model was superior to the basic CBR model. When four kinds of the adjustable parameters (i.e., MCAS, RAW, RCS, and TRCRMA/TRCRMS/TRCRSA) were applied to the filtering engine through the optimization process of the A-CBR model, its prediction accuracy was determined to be the highest (i.e., for estimating the compressive and tensile strength, 95.214% and 92.448% of the A-CBR (SVM&ANN) model, respectively) (refer to Table 5).

Table 6 and Table 7 show the optimized values of the adjustable parameters that were determined in the optimization process of the A-CBR model for estimating the compressive and tensile strength, respectively. It was shown that the optimized values of the adjustable parameters were determined very differently, which indicates that the filtering engine and the optimization process in the A-CBR model should be applied to overcome the disadvantage of the basic CBR model (i.e., relatively lower prediction accuracy than other conventional methodologies). As a result, it was determined that the A-CBR model can not only have the higher prediction accuracy that is the advantage of other methodologies (e.g., ANN and SVM), but also the higher explanatory power that is the advantage of the basic CBR model.

In conclusion, the A-CBR model was determined to be the most suitable approach for estimating the strength of sustainable concrete in the early construction phase. Furthermore, it is expected that the prediction accuracy of the A-CBR model will be further improved with the continuous accumulation of the case database.

Table 6 The optimized values of the adjustable parameters in estimating the compressive strength

| | Classification | A-CBR (MRA &ANN) | A-CBR (MRA &SVM) | A-CBR (SVM& ANN) |
|---|---|---|---|---|
| MCAS | | 39.41 | 62.30 | 33.09 |
| RAW | Concrete age | 0.00 | 0.00 | 0.00 |
| | Water | 58.43 | 0.00 | 2.54 |
| | Portland cement (PC) | 37.89 | 98.87 | 88.84 |
| | Portland limestone cement (LC) | 53.78 | 54.40 | 89.90 |
| | Fly ash | 46.81 | 74.13 | 18.35 |
| | Sand | 63.50 | 85.56 | 99.50 |
| | Coarse aggregate (CA) | 40.39 | 46.03 | 96.08 |
| | Lightweight aggregate (LWA) | 0.00 | 40.46 | 30.68 |
| | Air entraining-admixture (AEA) | 47.83 | 7.19 | 1.53 |
| RCS | | 12.00 | 6.00 | 19.00 |
| TRCRMA / TRCRMS / TRCRSA | | 9.19 | 9.13 | 6.25 |

Table 7 The optimized values of the adjustable parameters in estimating the tensile strength

| | Classification | A-CBR (MRA &ANN) | A-CBR (MRA &SVM) | A-CBR (SVM& ANN) |
|---|---|---|---|---|
| MCAS | | 37.74 | 28.38 | 85.60 |
| RAW | Concrete age | 1.00 | 41.37 | 97.46 |
| | Water | 98.91 | 74.36 | 0.00 |
| | Portland cement (PC) | 64.71 | 75.51 | 13.47 |
| | Portland limestone cement (LC) | 38.56 | 87.05 | 85.93 |
| | Fly ash | 0.00 | 4.63 | 0.00 |
| | Sand | 19.74 | 1.00 | 3.81 |
| | Coarse aggregate (CA) | 16.88 | 0.00 | 0.00 |
| | Lightweight aggregate (LWA) | 1.56 | 0.00 | 0.00 |
| | Air entraining-admixture (AEA) | 1.00 | 6.44 | 0.00 |
| RCS | | 7.00 | 3.00 | 2.00 |
| TRCRMA / TRCRMS / TRCRSA | | 6.48 | 13.43 | 13.80 |

### *4.2 Case Study for the case No.127*

The case No.127 was selected as a case study to illustrate the detailed estimation process for the strength of sustainable concrete using the developed A-CBR model. Table 8 shows the detailed description on the design variables for the mixture of concrete and the relevant compressive and tensile strength of the case No.127. Based on the A-CBR (SVM&ANN) model for estimating the compressive strength of the case No.127, the retrieval process of the developed A-CBR model can be explained in detail. As shown in Table 9, a total of seven similar cases (i.e., cases 92, 115, 134, 120, 79, 119, and 125) were finally selected for estimating the compressive strength of the case No.127. Table 10 shows that the average compressive strength of the seven similar cases was determined to be 56.237 MPa, resulting in 93.01% of the prediction accuracy compared to the actual value of the case No.127 (59.172 MPa). Through the aforementioned three-step processes of the developed A-CBR model (i.e., selecting the similar cases, filtering the selected cases, and improving the prediction accuracy), this study can estimate the compressive and tensile strength of the case No.127 (refer to Table 9).

Table 8 Design variables for the mixture of concrete and the relevant strength of the case No.127

| Classification | Value |
|---|---|
| (*Independent Variables*)Design variables for the mixture of concrete | |
| Concrete age | 90 (days) |
| Water | 215 (kg/m$^3$) |
| Portland cement | 520 (kg/m$^3$) |
| Portland limestone cement | 0 (kg/m$^3$) |
| Fly ash | 0 (kg/m$^3$) |
| Sand | 751 (kg/m$^3$) |
| Coarse aggregate | 246 (kg/m$^3$) |
| Lightweight aggregate | 243 (kg/m$^3$) |
| Air entraining-admixture | 137 (ml/m$^3$) |
| (*Dependent Variables*)Strength of concrete | |
| Compressive strength | 59.172 (Mpa) |
| Tensile strength | 0.049 (Mpa) |

Table 9 Summary of the retrieved similar cases using the A-CBR models for the concrete compressive and tensile strength of the case No.127

| Classification | Type of model | Case | Case No. | Case similarity score (%) | Strength (Mpa) | Prediction accuracy(%) |
|---|---|---|---|---|---|---|
| Compressive strength (CS)<br><br>For the case No.127, CS: 59.172 (Mpa) | A-CBR (MRA&ANN) | *RC 1 | 92 | 99.99 | 53.931 | 91.14 |
| | | RC 2 | 79 | 86.77 | 56.552 | 95.57 |
| | | RC 3 | 120 | 86.77 | 63.379 | 92.89 |
| | | RC 4 | 121 | 86.02 | 62.207 | 94.87 |
| | | RC 5 | 91 | 86.02 | 51.448 | 86.95 |
| | | RC 6 | 115 | 82.83 | 54.552 | 92.19 |
| | A-CBR (MRA&SVM) | RC 1 | 92 | 99.99 | 53.931 | 91.14 |
| | | RC 2 | 79 | 78.59 | 56.552 | 95.57 |
| | | RC 3 | 120 | 78.59 | 63.379 | 92.89 |
| | A-CBR (SVM&ANN) | RC 1 | 92 | 99.99 | 53.931 | 91.14 |
| | | RC 2 | 115 | 99.21 | 54.552 | 92.19 |
| | | RC 3 | 134 | 99.01 | 52.621 | 88.93 |
| | | RC 4 | 120 | 91.33 | 63.379 | 92.89 |
| | | RC 5 | 79 | 91.33 | 56.552 | 95.57 |
| | | RC 6 | 119 | 90.39 | 54.414 | 91.96 |
| | | RC 7 | 125 | 90.11 | 58.207 | 98.37 |
| Tensile strength (TS)<br><br>For the case No.127, TS: 4.069 (Mpa) | A-CBR (MRA&ANN) | RC 1 | 115 | 94.94 | 4.759 | 83.05 |
| | | RC 2 | 121 | 93.95 | 4.354 | 93.22 |
| | | RC 3 | 120 | 93.43 | 4.414 | 91.53 |
| | | RC 4 | 125 | 92.95 | 4.138 | 98.30 |
| | | RC 5 | 119 | 87.81 | 4.414 | 91.53 |
| | A-CBR (MRA&SVM) | RC 1 | 120 | 99.25 | 4.414 | 91.53 |
| | | RC 2 | 121 | 97.36 | 4.354 | 93.22 |
| | | RC 3 | 125 | 95.08 | 4.138 | 98.30 |
| | A-CBR (SVM&ANN) | RC 1 | 121 | 99.71 | 4.354 | 93.22 |

*RC stands for the retrieved case by using the A-CBR model.

Table 10 The retrieved similar cases for the compressive strength of the case No.127 using the A-CBR (SVM&ANN) model

| Case | Case No. | Concrete age (days) | Water ($kg/m^3$) | Portland cement ($kg/m^3$) | Portland limestone cement ($kg/m^3$) | Fly ash ($kg/m^3$) | Sand ($kg/m^3$) | Coarse aggregate ($kg/m^3$) | Lightweight aggregate ($kg/m^3$) | Air entraining-admixture ($ml/m^3$) | Case similarity score (%) | Compressive strength (Mpa) | Prediction accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Test Case | 127 | 90 | 215 | 520 | 0 | 0 | 751 | 246 | 243 | 137 | - | 59.172 | - |
| *RC 1 | 92 | 28 | 215 | 520 | 0 | 0 | 751 | 246 | 243 | 137 | 99.99 | 53.931 | 91.14 |
| RC 2 | 115 | 90 | 198 | 416 | 0 | 104 | 751 | 247 | 243 | 135 | 99.21 | 54.552 | 92.19 |
| RC 3 | 134 | 90 | 208 | 312 | 0 | 208 | 751 | 247 | 243 | 113 | 99.01 | 52.621 | 88.93 |
| RC 4 | 120 | 90 | 208 | 520 | 0 | 0 | 751 | 501 | 120 | 148 | 91.33 | 63.379 | 92.89 |
| RC 5 | 79 | 28 | 208 | 520 | 0 | 0 | 751 | 501 | 120 | 148 | 91.33 | 56.552 | 95.57 |
| RC 6 | 119 | 90 | 193 | 312 | 0 | 208 | 751 | 501 | 120 | 137 | 90.39 | 54.414 | 91.96 |
| RC 7 | 125 | 90 | 216 | 430 | 0 | 107 | 743 | 750 | 0 | 136 | 90.11 | 58.207 | 98.37 |
| Average compressive strength (predicted value) | | | | | | | | | | | | 56.237 | 93.01 |

*$RC$ stands for the retrieved case using the A-CBR model

## 5. Conclusions

Based on a thorough review of previous studies in investigating properties of concrete containing environmentally friendly materials, as well as modeling approaches to predicting sustainable concrete properties, this study aimed to develop an estimation methodology for the compressive and tensile strength of sustainable concrete using the A-CBR approach. Through the experimental studies, a total of 144 observations for the concrete strength were established, which were then used to develop the estimation model. As a result, the prediction accuracy of the A-CBR (SVM&ANN) model (i.e., 95.214% for compressive strength and 92.448% for tensile strength) was determined to be superior to other conventional methodologies including basic CBR, MRA, ANN, and SVM. In other words, it was proven that the A-CBR model can simultaneously provide the advantage of the conventional methodologies such as ANN and SVM (i.e., excellent prediction accuracy) as well as the advantage of the basic CBR model (i.e., provision of the predicted values with the retrieved historical-cases as references). In addition, considering the basic principal of the A-CBR model, the prediction accuracy of the A-CBR model could be expected to be further improved with the continuous accumulation of the case database.

The developed A-CBR model can help decision makers (e.g., ready-mix concrete supplier and precast concrete manufacturer) to easily and accurately establish the optimal concrete mixture design in the early construction phase. Different environmentally friendly materials can be incorporated in the A-CBR approach to estimating sustainable concrete properties. The developed methodology can be further extended to future research areas in sustainable concrete properties such as durability.

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