A Novel Evolutionary Learning to Prepare Sustainable Concrete Mixtures with Supplementary Cementitious Materials

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Research highlights

- A novel machine learning method called coyote optimization programming was introduced in this study.
- Applying optimization techniques to design concrete mixture proportions can reduce the unit cost by 36.6%.
- The introduced approach can decrease the global warming potential, energy consumption, and material consumption by 51%, 43%, and 11%, respectively.
- The application of supplementary cementitious materials in the concrete mixtures significantly enhances sustainability.

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Abstract

In this study, sustainable mixture designs of three concrete types, including fly ash concrete, silica fume concrete, and ground granulated blast furnace slag concrete, were investigated. To this end, the compressive strength formulas of each concrete type made with supplementary cementitious materials were obtained by introducing a new machine learning algorithm, called coyote optimization programming. The accuracy of this algorithm proved to be greater than that of conventional and recently-developed machine learning methods. An optimization problem is modeled, in which the compressive strengths, price, and environmental impact of the sustainable concrete mixture designs were estimated using global warming potential, energy consumption, and material consumption as the sustainability parameters. Results reveal that increasing the compressive strength reduces the sustainability of concrete, and thus, manufacturing concrete with a higher compressive strength than the one obtained from the design process contradicts the concrete's performance. Moreover, the 30-MPa sustainable fly ash concrete was proven to be the most sustainable mix with a gray relational grade of 1. This optimal mixture designed in this study can decrease the unit cost, global warming potential, energy consumption, and material consumption by 36.6%, 51%, 43%, and 11%, respectively.

Keywords

Coyote optimization programming; global warming potential; metaheuristic programming; sustainable mixture design; energy consumption.

1. Introduction

Concrete is the most used man-made material that has long been applied in the construction industry. The wide application of this construction material is due to its affordability, incombustibility, easy production, durability, and high modulus of elasticity (Aprianti S, 2017). In 2002, 12.6 billion tons of raw materials was used by the concrete industry to prepare different concrete mixtures (Mehta, 2002). Currently, more than 10 billion tons of concrete are annually produced (Meyer, 2009), resulting in the fabrication of more than one ton concrete per capita. It is estimated that the annual demand for concrete will grow to approximately 18 billion tons by 2050 (Mehta, 2002). As such, the environmental impacts caused by the extensive use of concrete and its ingredients derived from natural resources present a huge concern.

Hence, researchers have applied various technique to enhance various characteristics of concrete. Adhikary et al. (2021b) investigated the impact of carbon nanotubes on microstructural performance and compressive strength of lightweight aggregate concrete. In this regard, combination of silica aerogel particles and expanded glass was utilized as aggregate in the mixture proportion. The results indicated that microstructural performance and compressive strength of concrete increased using carbon nanotubes.

A practical technique from which the environmental impact of concrete can be considerably lessened is to improve the performance of concrete or employ waste materials (Adhikary et al., 2021a; Mehta and Ashish, 2020). As such, natural zeolite powder can improve mechanical and physical properties of concrete and as a result, it can reduce carbon footprint (Rudžionis et al., 2021). Similarly, aerogel can increase the compressive strength of concrete (Adhikary et al., 2021b). Moreover, supplementary cementitious materials (SCM) can be applied in the mixture to reduce the quantity of virgin materials and enhance the durability and mechanical properties of concrete (Ashish, 2019; Ashish and Verma, 2021). Most SCMs are obtained as the waste or by-products of the manufacturing of other products (Ashish and Verma, 2019a). Thus, the utilization of SCMs can reduce the need for raw materials as well as the environmental impact of concrete materials by lowering the amount of cement required in the mixture (Lothenbach et al., 2011).

Since the performance of SCMs in cementitious media is replacement ratio-dependent (Hendi et al., 2019; Miller et al., 2016; Shen et al., 2017), the optimal content of SCMs in concrete ingredients needs to be determined to enhance its sustainable production. The common techniques to optimally proportion concrete mixtures require experimentally-obtained data and using trial and error and, thus, the production and testing of numerous specimens (Ashish and Verma, 2019b). In the mixture design methods relied upon experimental data, cement is replaced with SCMs, and the ratio of replacement is selected among finite alternatives (Miller et al., 2016; Shen et al., 2017). Thus, much material is required to identify the optimum mixture design since a design method based on a limited number of experimental data would not be a suitable for designing eco-friendly or sustainable concrete. In this respect, machine learning approaches can be effectively utilized to overcome these deficiencies by reducing the usage of raw material.

A wide range of computational approaches and machine learning methods have been applied to predict the primary characteristics of concrete, such as compressive strength. That being said, artificial neural network (ANNs) (Qi et al., 2018), multi-gene genetic programming (Gandomi and Alavi, 2012), response surface methodology (RSM) (Hammoudi et al., 2019), combination of genetic programming with orthogonal least squares (Mousavi et al., 2010), extreme learning approach (Al-Shamiri et al., 2019), multivariate adaptive regression splines, M5 model tree (Amlashi et al., 2019), deep learning (Deng et al., 2018), hybrid ultrasonic-neural assessment (Sadowski et al., 2019), self-learning method (Yu et al., 2018), regression (Naseri, 2019), and fractional regression (Naseri et al., 2019) are commonly applied to recognize the relation between the compressive strength of concrete and mixture design.

However, most machine learning methods are regarded as black-box tools, or in other words, obtaining the equation of inputs and outputs is not possible (Gandomi et al., 2015). Moreover, the accuracy of formulations achieved by regressions and multiple regressions is not ideal, and these classical methods may not be reliable enough (Mirzahosseini et al., 2019). As such, developing accurate algorithms to predict the compressive strength of concrete by evolutionary prediction algorithms (capable of generating the optimal formulation) is of great importance in designing environmentally-friendly concrete. In this regard, Naseri et al. (2021) proposed a new approach to optimize the mixture design of sustainable concrete containing fly ash. A new machine learning algorithm, Marine Predator Programming, was introduced for predicting concrete characteristics. Non-hazardous waste disposed, hazardous waste disposed, radioactive waste disposed, and global warming potential, were considered environmental parameters, and minimized in an optimization problem. The results indicated that sustainable mixture proportions could significantly reduce the sustainability index by over 80%.

Zhang et al. (2021) investigated optimizing the mixture design of lightweight foamed concrete. The least squares support vector regression was applied to predict the concrete characteristics. Subsequently, the firefly algorithm was used to optimize the concrete mixture design. Naseri et al. (2020b) introduced three novel machine learning techniques, including water cycle programming, genetic programming, and soccer league competition programming, to predict the compressive strength of ordinary Portland cement concrete. These methods could generate the equation of compressive strength based on the weights of the utilized materials.

While the accuracy of the latter-mentioned metaheuristic algorithms proved to significantly greater than that of conventional prediction techniques, the preparation of concrete containing SCMs was not considered in their study. Moreover, the application of recently-developed metaheuristic algorithms to produce robust machine learning methods has been overlooked.

This study aims to optimize the mixture design of sustainable concretes. Since most conventional prediction techniques are black-box tools and cannot generate equations, they cannot easily be used in the concrete mixture proportion optimization problem. In this regard, a new prediction method is proposed to predict the compressive strength of concrete and present the compressive strength equation based on the mixture ingredients. Although optimizing the mixture design of ordinary Portland cement concrete by optimization techniques has been investigated, designing the mixture proportion of sustainable concretes by computational techniques has not received enough attention. To this end, three types of SCMs, including fly ash, silica fume, and ground granulated blast furnace slag, are used in mixture proportioning to reduce the content of cement and design sustainable mixtures. Consequently, compressive strength and different environmental parameters, including global warming potential, energy consumption, and material consumption, are applied in the optimization process to find the optimal mixture design of sustainable concretes for different compressive strength classes. Ultimately, gray relational analysis is performed to prioritize the designed mixtures.

2. Research plan

Although the concrete industry is responsible for causing significant environmental pollution, estimating and designing the best proportion of sustainable concrete has not received enough attention. As such, the harmful effects of the industry on the environment can considerably be reduced by implementing sustainable production strategies, such as replacing standard concrete ingredients with greener materials.

Based on the concepts mentioned above, eco-friendly concrete is defined as concrete with low levels of global warming potential (GWP) emission, energy consumption (EC), and material consumption (MC) in this investigation. Sustainable concrete is regarded as being eco-friendly with a high level of compressive strength and minimum feasible cost. Even though classical methods can estimate compressive strength, they are not sufficiently accurate or capable of providing the formulation of compressive strength to determine the optimal mixture design. Hence, they can be applied to design the concrete mixture proportion. Since designing sustainable concrete containing SCMs by novel computational approaches and machine learning methods has been neglected, the presented study proposes a novel machine learning method to overcome these limitations. That is, the introduced prediction algorithm is a white-box method, and it can present the equation of the compressive strength based on concrete's the mixture ingredient. Besides, the precision of the introduced technique is comparable with the most precise prediction methods.

As previously stated, cement is a sort of harmful material to the environment, and as such, three types of SCMs, including fly ash, silica fume, and ground granulated blast furnace slag, are used in mixture proportioning to reduce the content of cement in the concrete mixes. In addition, in the current study, concrete mixtures are classified into three groups, including fly ash concrete (FL-C), silica fume concrete (SF-C), and ground granulated furnace blast slag concrete (GGBFS-C) and the sustainable mixture proportion of these mixtures is then investigated.

Previous studies on developing eco-friendly concrete using SCMS attempted to identify the most sustainable concrete mixture proportion among finite mixtures. In this respect, due to the wide range of available concrete ingredients, selecting the optimal mixture design of eco-friendly concrete among a finite number of mixture designs may not be practical. Thus, an extensive range of materials and their quantity was considered in order to investigate the optimal content of concrete ingredients. In addition, the current study evaluated the essential sustainability parameters, including the compressive strength, unit price, and environmental impacts (via GWP, EC, and MC, respectively) as the primary objectives of the model to reduce the impacts of the concrete industry on the environment and to manufacture economical concrete. Hence, the sustainability parameters were regarded as the objective functions of the optimization problem, and the model analyzed a mixture design of the most sustainable concrete with different compressive strengths, including 30, 40, 50, and 60 MPa. Finally, gray relational analysis (GRA) was performed to compare the mixtures based on their sustainability characteristics and to identify the most sustainable mixture for each compressive strength class.

3. Methods and materials

The goal of the current study aimed to establish a method for designing sustainable concrete containing SCMs. To this end, reliable experimental data, including various concrete mixtures incorporating different types of SCMs and their corresponding 28-day compressive strengths, were collected. New prediction techniques were employed to generate the most accurate compressive strength formula for each concrete type. After obtaining the equations of the compressive strength, cost, GWP, EC, and MC, the mixture proportions of sustainable concrete for each type of SCM and each compressive strength class were achieved through an optimization problem. Finally, the proposed sustainable concrete mixture proportions in each compressive strength class were compared based on the examined sustainability parameters by virtue of GRA. The flowchart of the methodology is depicted in Fig. 1.

Fig. 1

3.1. Data preparation

This investigation utilized 1200 experimentally-obtained data of the compressive strength of various concrete mixtures to estimate the mixture proportions of sustainable concrete incorporating various SCMs. These data were extracted from authentic international publications (Bhanja and Sengupta, 2005; Çakır and Sofyanlı, 2015; Chang et al., 1996; M.F.M. Zain, M.R. Karim, M.N. Islam, M.M. Hossain and Al-Mattarneh, 2015; Mazloom et al., 2004; Özcan et al., 2009; Yeh, 1999, 1998). For consistency, all the compressive strength data obtained from the testing of different concrete sample sizes were converted into the compressive strength of a 15 cm × 30 cm (diameter × height) cylinder, which is the standard sample size for concrete mixture designs, according to Yi et al. (2006). Data were then divided into training and testing datasets to gauge the capability of machine learning methods and estimate the compressive strength of each concrete type. The inputs included the age of specimens, quantity (kg/m^3) of concrete materials (including water, cement, fine aggregate, coarse aggregate, superplasticizer, and SCMs), and the weight ratios of water to binder (cement + SCM), SCM to binder, coarse aggregate to binder, fine aggregate to total aggregate, and superplasticizer to binder. The compressive strength of concrete was regarded as the output of the prediction models.

Since the range of inputs and the output differ, they should be scaled to the same range (Shirzadi Javid et al., 2020). Contrary to common techniques, the data were not scaled from 0 to 1 because the prediction models can select logarithmic functions. Hence, all the data were scaled between 0.1 and 0.9 using Eq. (1):

$$S_i = 0.1 + (0.9 - 0.1) \times \frac{i - i_{min}}{i_{max} - i_{min}} \quad (1)$$

where i is the initial value; S_i is the scaled value; and i_{min} and i_{max} are the minimum and maximum values in the dataset, respectively. The standard deviation, maximum, minimum, and average values of the initial data are presented in Tables 1-3 for various SCMs. As previously stated, concrete mixtures were classified into three groups regarding the type of SCM. In addition, the characteristics of the input and output variables of fly ash concrete (FL-C), silica fume concrete (SF-C), and ground granulated blast furnace slag concrete (GGBFS-C) are given in Table 1, Table 2, and Table 3, respectively.

Insert Tables 1 to 3.

3.2. Compressive strength prediction models

A novel machine learning technique called coyote optimization algorithm programming (COP) was developed in this investigation to estimate the compressive strength of concrete mixtures with various SCMs. The outcomes of the introduced method were then compared with the results obtained by deep learning (DL), as a robust prediction method, and by water cycle algorithm programming (WCP) developed by Naseri et al. (2020b), which was developed to predict the compressive strength of ordinary Portland cement concrete. The results indicate that the precision of WCP (R^2=0.93) is greater than the accuracy of soccer league competition programming (R^2=0.89), genetic programming (R^2=0.87), support vector machine (R^2=0.80), artificial neural network (R^2=0.90), and linear regression (R^2=0.46). Accordingly, WCP, as a precise and powerful prediction model, was employed to estimate the compressive strength of concrete containing SCMs. Meanwhile, the COP was compared with WCP based on precision indicators to assess its accuracy. Consequently, for each type of concrete, the most accurate model was selected among the mentioned machine learning techniques to optimize the mixture proportions of concrete incorporating SCMs. The details of the machine learning methods employed in this study are provided in the following sections.

3.2.1. Coyote optimization programming

This study introduces coyote optimization programming (COP) inspired by the coyote optimization algorithm (COA) as a novel prediction metaheuristic-based programming, which is a machine learning technique used for prediction. This technique is highly qualified to find the correlation between the output and inputs of models. These metaheuristic-based machine learning models advantageously generate an equation for the output based on the inputs of the model, and thus, the precision of these algorithms is desired (Mirzahosseini et al., 2019).

COA was introduced in 2018 and has shown to be a powerful algorithm for solving global optimization problems (Pierezan and Coelho, 2018). In this algorithm, the solution vectors and fitness values of corresponding solution vectors are associated with coyotes and their social behavior, respectively. Naturally, coyotes divide into different groups, where the most valuable coyote (or solution vector) is called the alpha coyote in each group. Each coyote transfers culture among its groupmates and is affected by the leader of the group (alpha) and other groupmates. In this respect, each solution vector is moved towards the best solution vector of its group and the center gravity of other solution vectors available in its group. As coyotes of different groups are replaced in order to transfer various cultures, the vectors, by following this pattern, help the algorithm to cover more area in the feasible region. Additionally, the worst coyotes (the weakest solution vectors) are removed from the society and replaced with the new generation, and thus, the new population is generated by the combination of current coyotes in different groups (Pierezan et al., 2019). Figure 2 displays the schematic flow chart of the coyote optimization algorithm, including the following primary steps:

1. The coyotes (solution vectors) are divided into different herds (groups). The coyotes are ranked based on their power (fitness value) in each group, and the dominant coyote (current best solution vector) is denoted the alpha.
2. The culture is transferred among coyotes and their groupmates. In other words, the solution vectors move towards other solution vectors, and this movement is based on the fitness value of solution vectors.
3. Some of the coyotes are transferred to different groups to investigate more spaces in the feasible area.
4. The worst coyotes are removed from the society, and new coyotes are born. Ultimately, the algorithm goes back to the first step.

Fig. 2.

Primarily, COA was adapted for integer programming problems to develop COP. Subsequently, three decision variables were assigned to each input of the problem, each representing the served functions, while the other decision variables generated the coefficient of the corresponding input. The served functions included trigonometric functions (sin, cos, tan, and cot), logarithmic functions with different bases, exponential functions, and various forms of radical functions. 20 various modes were considered for each decision variable. Hence, each input's format was selected from 8000 unique selections because three decision variables (one served function and two coefficient generators), including 20 modes, were allocated to each input. Furthermore, 400 different integration functions were taken into account as the integration of inputs to generate the equation of the compressive strength based on the content of concrete ingredients and their ratios. In other words, two decision variables were employed to determine the optimal integration function. Four different modes were allocated to constant values and combined with the integration functions, increasing the number of integration functions to 64 million forms to enhance the efficiency of the models. This process significantly expands the feasible region and drastically increases the probability of finding better solutions. The mean absolute error of the compressive strength of concrete was set as the objective function of the metaheuristic algorithms with the purpose to minimize the mean absolute error of the testing data.

3.2.2. Water cycle programming

Water cycle programming (WCP) is a newly developed machine learning method originating from the water cycle algorithm (WCA). As previously mentioned, WCP proved to outperform soccer league competition programming, genetic programming, support vector machine, artificial neural network, and linear regression in estimating the compressive strength of ordinary Portland cement concrete (Naseri et al., 2020b). Accordingly, this robust method was employed in this study to predict the compressive strength of concrete containing various SCMs. WCP was generated by converting WCA, as an optimization algorithm, into a prediction technique in the same manner that COA was converted into COP.

The water cycle algorithm was inspired by the cycle of water in the earth (Naseri et al., 2021c), in which each vector solution is regarded as a raindrop. These raindrops are ranked according to their corresponding fitness values, and the best raindrop is assigned to the sea, and subsequent raindrops are associated with rivers and then streams. In each iteration, the rivers flow into the sea, and the streams flow into the sea and rivers. Consequently, the positions of solution vectors are updated. Besides, the evaporation operator generates new data when solution vectors accumulate in small zones in the feasible region (Sadollah et al., 2015). As a metaheuristic optimization algorithm is applied to develop COP, the algorithm is run five times (Naseri et al., 2018). Afterward, the solution with the lowest objective function value is considered the problem's optimal solution. Figure 3 illustrates the flowchart of the water cycle algorithm (Naseri et al., 2020b), which is described in detail as follows:

1. Initially, the fitness values of data are gauged and classified into the sea, rivers, and streams based on their qualification.
2. The streams move toward the sea and rivers to search in better spaces.
3. The rivers are transferred to the adjacent areas of the sea in order to investigate more valuable regions.
4. If the distances between the sea and rivers or the distances between the sea and streams are lower than a specific value, the evaporation operator is run to abandon the local-minimum area.
5. Afterwards, new data are generated by a raining operator and then compared with the previous data. The most valuable data remain, and the others are eliminated.

Subsequently, the algorithm returns to the first step.

Fig. 3.

3.2.3. Deep learning

Deep learning (DL) is a multi-layer artificial neural network inspired by mammalian brain recognition that applies multi-layer transfer functions. Accordingly, the model's inputs can be combined in a nonlinear space (Deng et al., 2018). In DL, the education system does not depend on artificial feature selection, and the data presentation features are spotted autonomously, and complex nonlinear functions can be learned (Wei et al., 2019).

3.3. Optimization problem formulation

3.3.1. Compressive strength formula

As previously stated, three machine learning techniques were employed to model the compressive strength of various concrete types containing SCMs. Subsequently, the precision of these models was compared based on different performance indicators to identify and subsequently utilize the most accurate model to design the mixture proportion of sustainable concrete for various compressive strength classes.

Testing data precision is considered the most critical parameter when selecting the most accurate model. Six performance indicators, including correlation coefficient (R), mean square error (MSE), mean absolute error (MAE), coefficient of determination (R^2), root mean square error (RMSE), and the percentage of mixtures with a MAE less than 30% (E30), were considered to compare the machine learning methods and find the most accurate model. The equations for R, MSE, MAE, R^2, RMSE, and E30 are indicated in Eq. (2) to (7), respectively:

$$R = \frac{\sum_{i=1}^{n}(EXP_i - \overline{EXP_i}) \times (PRE_i - \overline{PRE_i})}{\sqrt{\sum_{i=1}^{n}(EXP_i - \overline{EXP_i})^2 \times \sum_{i=1}^{n}(PRE_i - \overline{PRE_i})^2}} \tag{2}$$

$$MSE = \frac{\sum_{i=1}^{n}(EXP_i - PRE_i)^2}{n} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{n} \left| EXP_i - PRE_i \right|}{n} \tag{4}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} (EXP_i - \overline{EXP_i}) \times (PRE_i - \overline{PRE_i})}{\sqrt{\sum_{i=1}^{n} (EXP_i - \overline{EXP_i})^2 \times \sum_{i=1}^{n} (PRE_i - \overline{PRE_i})^2}} \right)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (EXP_i - PRE_i)^2}{n}} \tag{6}$$

$$E30 = \frac{(number \text{ of mixtures that their percentage MAE is less than 30\%}) \times 100}{n} \tag{7}$$

where EXP_i is the compressive strength of concrete based on experimental test results; $\overline{EXP_i}$ represents the average value of the compressive strength of concrete obtained from the experimental test results; PRE_i is the estimated compressive strength; $\overline{PRE_i}$ indicates the average value of estimated compressive strength; and n is the number of samples.

3.3.2. Sustainable criteria formulation

In addition to the 28-day compressive strength equation, the price of concrete constituents per cubic meter of concrete and the environmental impacts, including GWP, EC, and MC, were selected as the sustainability parameters. In the optimization model, the 28-day compressive strength is regarded as a constraint. With that said, the equation relevant to the most accurate model was considered a constraint and set to 30, 40, 50, and 60 MPa. Consequently, the model was ran in order to estimate the mixture designs of sustainable concrete for each compressive strength class (30, 40, 50, and 60 MPa). Cost and MC are the total price and total weight of concrete ingredients to manufacture one cubic meter of concrete, respectively. GWP is the summation of global warming potential emitted during the production of concrete and its ingredients, and EC is the total amount of energy required to manufacture concrete and its ingredients. The objective functions of cost, GWP, EC, and MC are presented in Eqs. (8), (9), (10), and (11), respectively. The environmental objective function is the combination of GWP, EC, and MC, as shown in Eq. (12).

$$\text{Cost} = (U_{CE} \times CE) + (U_{WA} \times WA) + (U_{SP} \times SP) + (U_{CA} \times CA) + (U_{FA} \times FA) + (U_{FL} \times FL) + (U_{SF} \times SF) + (U_{SL} \times SL) \quad (8)$$

$$GWP = (C_{CE} \times CE) + (C_{WA} \times WA) + (C_{SP} \times SP) + (C_{CA} \times CA) + (C_{FA} \times FA) + (C_{FL} \times FL) + (C_{SF} \times SF) + (C_{SL} \times SL) \quad (9)$$

$$EC = (E_{CE} \times CE) + (E_{WA} \times WA) + (E_{SP} \times SP) + (E_{CA} \times CA) + (E_{FA} \times FA) + (E_{FL} \times FL) + (E_{SF} \times SF) + (E_{SL} \times SL) \quad (10)$$

$$MC = CE + WA + SP + CA + FA \quad (11)$$

$$Environment = (\omega_1 \times GWP) + (\omega_2 \times EC) + (\omega_3 \times MC) \quad (12)$$

where U_{CE}, U_{WA}, U_{CA}, U_{FA}, U_{SP}, U_{FL}, U_{SF}, and U_{SL} are the unit price of cement, water, coarse aggregate, fine aggregate, superplasticizer, fly ash, silica fume, and GGBFS, respectively. Moreover, CE, WA, CA, FA, SP, FL, SF, and SL are the weights of cement, water, coarse aggregate, fine aggregate, superplasticizer, fly ash, silica fume, and GGBFS in the mixture design, respectively. C_{CE}, C_{WA}, C_{CA}, C_{FA}, C_{SP}, C_{FL}, C_{SF}, and C_{SL} represent the GWP emitted during the production process of cement, water, coarse aggregate, fine aggregate, superplasticizer, fly ash, silica fume, and GGBFS, respectively. E_{CE}, E_{WA}, E_{CA}, E_{FA}, E_{SP}, E_{FL}, E_{SF}, and E_{SL} are the amounts of energy consumed to produce one kilogram of cement, water, coarse aggregate, fine aggregate, superplasticizer, fly ash, silica fume, and GGBFS, respectively. In Eqs. (8) to (11), the amount of materials equals zero if they do not exist in the mixture design. For instance, the value of SF, and SL are equal to zero in FL-C. Besides, ω_1, ω_2, and ω_3 are the weight coefficients of GWP, EC, and MC in the environment objective function. According to Fuente et al. (2017), ω_1, ω_2, and ω_3 are 0.4, 0.3, and 0.3, respectively, which were utilized in Eq. (12). The unit price of the materials in the United States, and their EC, GWP, and specific gravity are presented in Table 4. These values were extracted from previous studies (Assi et al., 2018; Chiaia et al., 2014; Grist et al., 2015; Long et al., 2015; Müller et al., 2014; Pineda et al., 2017; Wille and Boisvert-Cotulio, 2015).

Table 4

To incorporate all the sustainability parameters in a single objective function, all parameters, including GWP, EC, MC, and cost, were scaled to a similar range. Eq. (1) was applied to scale the mentioned criteria to the desired range. Accordingly, the objective function of the environment was automatically scaled between 0.1 and 0.9. The minimum and maximum of the sustainability parameters were considered the maximum and minimum values spotted in the initial mixture proportions because the machine learning methods are interpolation-based techniques. The maximum and minimum values of the sustainability parameters for different concrete types are shown in Table 5.

Table 5

3.3.3. Optimization modeling

Optimization of concrete mixture design is vital (Khan et al., 2017). Meanwhile, sustainability should be considered in concrete mixture proportioning and material selection (Aguado et al., 2012; Zhong et al., 2017). In this work, sustainability was the objective function of the optimization model with the goal to enhance sustainability in designing concrete mixtures. As such, an appropriate objective function should be set to simultaneously improve all the sustainability parameters. The environmental objective function integrates all the environmental impacts based on Eq. (12). To unify the impacts of cost and environmental impacts, the quadratic distance to the ideal level is regarded as the form of the objective function of the optimization problem presented in Eq. (13) (Naseri et al., 2020a). Besides, the optimization function contains some constraints to increase the sensibility of the model. There are four constraints in the optimization model, including the range of inputs, range of sustainability parameters, unit volume of concrete, and the 28-day compressive strength of concrete, which are calculated by Eqs. (14), (15), (16), and (17), respectively:

$$\left(\text{minimize}\right)\ z = (Environment - ideal\ \ level)^2 + (\text{Cos}t - ideal\ \ level)^2 \tag{13}$$

$$\begin{aligned} &s\ .t: \\ &input_i \in [0.1, 0.9] \qquad \forall \text{i} \in \{1,2,...,\text{k}\} \end{aligned} \tag{14}$$

$$output_j \in [0.1, 0.9] \qquad \forall j \in \{1,2,...,\mathrm{m}\} \tag{15}$$

$$Volume = \frac{CE}{\rho_{CE}} + \frac{WA}{\rho_{WA}} + \frac{SP}{\rho_{SP}} + \frac{FA}{\rho_{FA}} + \frac{CA}{\rho_{CA}} + air\ void \tag{16}$$

$$CSD = r \qquad \forall r \in \{30,40,50,60\} \tag{17}$$

where $ideal\ level$ is the desired value of each objective function, which are scaled from 0.1 to 0.9. As such, the $ideal\ level$ equals 0.1 in Eq. (13), implying the minimum values of the sustainability parameters within their allowed range. $input_i$ is the input variable of the model, including the scaled values of the weights of concrete ingredients and the scaled values of the ingredient weight ratios. $output_j$ implies the outputs of the model, which are sustainability parameters, including the scaled values of GWP, EC, and MC, environmental objective function, and cost. i and j are the number of inputs and sustainability parameters of the model, respectively. ρ_{CE}, ρ_{WA}, ρ_{SP}, ρ_{FA}, and ρ_{CA} are the specific gravities of cement, water, superplasticizer, fine aggregate, and coarse aggregate, respectively, as shown in Table 4. To design the concrete mixture, the weight of its ingredients should be determined by considering the concrete volume constraint equals one cubic meter, which is presented in Eq. (16). In this equation, $air\ void$ is the volume of entrapped air that entered the concrete matrix during the mixing and casting processes. According to ACI 211.1, $air\ void$ is regarded as 2%. Moreover, CSD and r are the 28-day compressive strength of concrete and the classes of compressive strength considered in the current study, respectively. Note that, in this paper, the primary objective is to estimate the mixture design of sustainable and eco-friendly concrete with compressive strengths equal 30, 40, 50, and 60 MPa. Thus, these values are assigned to the parameter r .

After estimating mixture designs, the mixtures were compared based on sustainability and eco-friendliness characteristics regarding GWP, EC, and MC as the environmental factors. Furthermore, gray relational analysis (GRA) was conducted, according to Panda et al. (2016), to prioritize the mixtures based on their sustainability.

4. Results and discussion

The results of this study are presented in three parts. In the first section, the precision of the introduced methods and the conventional machine learning models are compared, and the most accurate model for each concrete type is selected. Furthermore, the compressive strength equation for the concrete containing various SCMs based on the quantity of the ingredients and their ratios are given in this part. In the second section, the mixture design of sustainable concretes is presented and compared based on the sustainability parameters. The environmental impacts of the mentioned mixes are scrutinized, and the eco-friendly mixture designs are analyzed based on their environmental impacts. In addition, the optimal contents of supplementary cementitious materials for each compressive strength class of sustainable concretes are presented. In the last part, using GRA, the sustainability of various concrete types is assessed, and the most sustainable mixture for all compressive strength classes is introduced. Moreover, the sustainable mixtures are ranked based on their sustainability parameters (i.e., cost and eco-friendliness characteristics).

4.1. Prediction of the compressive strength

In this study, by virtue of the robustness and potency of metaheuristic algorithms, a novel machine learning technique (COP) is proposed to predict the compressive strength of concrete mixtures incorporating SCMs. The precision of this novel method was then compared with powerful machine learning methods, including WCP and DL. Afterwards, the most accurate model of compressive strength for each concrete type containing SCMs was chosen for the mixture design of sustainable concrete prediction.

The accuracy of the proposed and conventional prediction methods were assessed based on various performance indicators, including correlation coefficient (R), mean square error (MSE), mean absolute error (MAE), coefficient of determination (R^2), root mean square error (RMSE), and the percentage of mixtures with MAE less than 30% (E30). The values of the performance indicators were then compared based on testing data in order to detect the most accurate model, since these machine learning models are applied to estimate the compressive strength of unseen data and the prediction power is much more important than the training phase. Subsequently, external validation was applied to verify the performance of the prediction models, using persuasive models, including regression line slope (k and k'), confirmation indicator (R_m), and performance index (m and n), were utilized as external validation parameters. These external validation indicators were computed based on the procedures introduced by Tropsha et al. (2003) and Golbraikh and Tropsha (2002).

4.1.1. Prediction of the compressive strength of FL-C

The error histogram of machine learning techniques for testing data is displayed in Fig. 4. Furthermore, the MAE, RMSE, R, R^2, and E30 of prediction models for estimating the compressive strength of FL-C are presented in Fig. 4. As can be perceived from the results in Fig. 4, the least amount of MAE and RMSE for testing data are related to COP, which are equal to 3.07 and 3.69 MPa, respectively. The performance of COP, WCP, and DL are acceptable because their MAE for testing data is less than 4 MPa. Thus, it can be postulated that COP is the most accurate model to predict the compressive strength of FL-C. Moreover, the highest level of R, R^2, and E30 for testing data are connected with COP, with respective values of 96%, 93%, and 95%. These results further illustrate that COP is qualified to predict the compressive strength of FL-C with an error less than 30% for 95% of the testing data. Hence, it is suggested that the precision of COP is higher than that of other machine learning techniques for estimating the compressive strength of FL-C mixtures. Specifically, COP estimated the compressive strength of 76.8% of the testing data with an error less than 5 MPa.

To validate the results of the performance indicators, results of the external validation are shown in Table 6. As can be seen, k and k' of all applied prediction models are between 0.85 and 1.15. Meanwhile, m and n indices are lower than 0.1 in all models for training and testing data. R_m of all prediction methods is higher than 0.5. Therefore, the results of the used prediction models are validated, which shows that COP, WCP, and DP are competent to be applied to estimate the compressive strength of FL-C. As such, it can be hypothesized that COP is the most accurate model, and thus, its generated equation was applied to estimate the mixture design of FL-C. Also, the compressive strength equations based on mixture proportion obtained by COP and WCP are provided in Eqs. (18) and (19), respectively.

Fig. 4.

$$CS_{COP-FL} = \frac{(\sqrt{5} \times \tan(S_{CE})) + (-0.5 \times S_{SP}^{3}) + (0.3 \times \sqrt[3]{3} \times \exp(S_{FL})) + (0.2 \times \sqrt{5} \times \sqrt[3]{S_{CA}})}{(0.9 \times \sqrt{7 \times S_{WA}}) + (0.675 \times S_{AG}^{-1}) + 0.7} + \sin((-0.375 \times \log(S_{WABI})) + (-0.15 \times \tan(S_{FLBI})) \times \cos((-0.5 \times \sqrt{3} \times S_{SPBI}) + (0.2 \times \cot(S_{FATA}))) \quad (18)$$

$$CS_{WCP-FL} = \exp((0.7 \times \sqrt[3]{2} \times \log_2^{S_{CE}}) + (0.9 \times \sqrt[3]{3} \times \tan(S_{FL})) + (-0.675 \times \sin(S_{WA})) + (-0.4 \times \sqrt[3]{4} \times 2^{S_{SP}})) + \exp((0.2 \times \sqrt{7} \times \log^{S_{CA}}) + (0.35 \times S_{FA}) + (-0.1 \times \sqrt{6} \times S_{AG}^{-1}) - 0.675) + (((-0.3 \times \sqrt[3]{4} \times \log_2^{S_{WABI}}) + (-0.375 \times \sqrt{3} \times S_{FLBI})) \times ((0.45 \times 2^{S_{SPBI}}) + (0.75 \times \cos(S_{FATA}))) \times ((0.15 \times \sin(S_{CABI})) + 0.175))$$

(19)

where CS_{COP-FL} and CS_{WCP-FL} are the scaled values of the compressive strength of FL-C provided by COP and WCP techniques, respectively. S_{CE}, S_{FL}, S_{WA}, S_{SP}, S_{CA}, S_{FA}, S_{AG}, S_{WABI}, S_{FLBI}, S_{SPBI}, S_{FATA}, and S_{CABI} are the scaled values of cement, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, age, water to binder ratio, fly ash to binder ratio, superplasticizer to binder ratio, fine aggregate to total aggregate ratio, and coarse aggregate to binder, respectively.

Table 6.

4.1.2. Prediction of the compressive strength of SF-C

The precision and error histogram of the prediction methods applied to estimate the compressive strength of SF-C are illustrated in Fig. 5, where the performance indicators, including MAE, RMSE, R, R^2, and E30, were used to compare the machine learning techniques and determine the most accurate model. Based on Fig. 5, COP is the most precise model, followed by WCP and DL. The MAE and RMSE of COP for the testing data are 3.69 and 4.44 MPa, respectively, which are far less than those of other machine learning techniques. Additionally, MAE values of WCP and DL for the testing data are 3.93 MPa and 4.47 MPa, respectively, indicating that the performance of the proposed technique (COP) is better than that of other methods. According to the results illustrated in Fig. 5, COP provides the highest level of the testing data R^2 (94%) and outweighs the other prediction models. The E30 of COP and WCP is equal to 1, signifying that the performance of these methods is satisfactory. These two techniques estimated the compressive strength of all testing data with an error less than 30%. A more detailed look at the results in Fig. 5 indicates that COP is the most powerful model because it predicts the compressive strength of 77% of data with an error less than 5 MPa, while WCP and DL predicted 66% and 64% of the data with an error less than 5 MPa, respectively. The outcomes of this error analysis are in harmony with the results of other performance indicators, and therefore, it can be postulated that COP is the best model to predict the compressive strength of SF-C.

The results of the external validation indicators for SF-C are shown in Table 7, which are in line with the outcomes of the performance indicators. The validation process represents that COP, WCP, and DL are validated since their corresponding validation performance indicators are located in the ideal ranges. Further, it can be realized that COP, WCP, and DL are capable of predicting the compressive strength of silica fume concrete. The equations of compressive strength of silica fume concrete (SF-C) generated by COP and WCP are presented in Eqs. (20) and (21), respectively:

Fig. 5.

$$
\begin{aligned}
CS_{COP-SF} = {} & \frac{(0.3\times\sqrt{7}\times\log^{S_{CE}})+(1.2\times\cos(S_{SP}))+(0.25\times\sqrt{3}\times S_{SF})+(0.25\times\sqrt[3]{S_{CA}})}{(1.125\times\exp(S_{WA}))+(0.1\times S_{AG}^{-1})-0.2}+(((0.225\times\sqrt{S_{WABI}})+ \\
& (-0.15\times\log^{S_{SFBI}}))\times((0.2\times\sqrt{6}\times\exp(S_{SPBI}))+(0.35\times 3^{S_{FATA}}))\times((-0.4\times\sqrt{6}\times\cos(S_{CABI}))+0.225))
\end{aligned}
\tag{20}
$$

$$
\begin{aligned}
CS_{WCP-SF} = {} & \exp((0.875\times\sqrt{S_{CE}})+(0.5\times\log_2^{S_{SF}})+(-0.7\times\sqrt{10}\times S_{WA})+(-0.5\times 4^{S_{SP}}))+\exp((0.8\times\sqrt[3]{3}\times\sqrt{S_{CA}}) \\
& +(0.45\times\log^{S_{FA}})+(-0.15\times S_{AG}^{-1})-\sqrt[3]{4})+(((-0.75\times S_{WABI})+(0.4\times\sqrt[3]{3}\times\cos(S_{SFBI})))\times((0.225\times 3^{S_{SPBI}}) \\
& +(-0.8\times\cos(S_{FATA})))\times((-\cos(S_{CABI}))-0.025))
\end{aligned}
\tag{21}
$$

where CS_{COP-SF} and CS_{WCP-SF} are the scaled values of the compressive strength of silica fume concrete (SF-C) predicted by COP and WCP techniques; and S_{SF} and S_{SFBI} are the scaled values of silica fume weight and silica fume to binder ratio in the mixture design, respectively. According to the aforementioned concepts, COP is the most accurate model in estimating the compressive strength of SF-C. Accordingly, Eq. (20) was utilized in the optimization modeling to design sustainable SF-C mixtures.

Table 7.

4.1.3. Prediction of the compressive strength of GGBFS-C

The performance and error histogram of the proposed and conventional machine learning techniques to predict the compressive strength of GGBFS-C are illustrated in Fig. 6. As can be seen, MAE and RMSE of COP are 4.40 and 5.98 MPa, which are significantly lower than those of other methods; thus, COP provides the highest accuracy. The MAE values for WCP and DL are 4.86 and 6.49 MPa, respectively. According to the values of R, R^2, and E30 in Fig. 6, COP is the only model with an R and E30 of the training data greater than 90%. The R, R^2, and E30 of the training data for COP technique equal 91%, 84%, and 91%, respectively. That being said, there is a strong correlation between the experimental test results and the values predicted by COP. Additionally, the COP prediction model achieved 91% of the data with a percentage error less than 30%. Thus, the most powerful machine learning method to estimate the compressive strength of GGBFS-C is COP based on the values of R, R^2, and E30. As can be perceived from the results shown in Fig. 6, COP provides the highest precision and is highly qualified to predict the compressive strength of GGBFS-C. The COP estimated the compressive strength of 68% of the testing data with an error less than 5 MPa, indicating that there is a positive correlation between the experimental test results and the values estimated by COP. However, the performances of WCP and DL are not desired, which estimated 60% and 54% of the testing data with an error less than 5 MPa.

The external validation was performed to analyze the results presented by the performance indicators and error histogram analysis. The results of external validation related to GGBFS-C are presented in Table 8. According to the testing data confirmation indicator (R_m), COP was validated and is favorably capable of estimating the compressive strength of GGBFS-C. Nevertheless, the results of other prediction models were not verified, and their results may not be trustworthy. Hence, DL and WCP may not be appropriate methods to predict the compressive strength of GGBFS-C since their results are not verified by the confirmation indicator (R_m). Accordingly, COP was selected as the best prediction model for GGBFS-C data, and the equation generated by COP was applied to design sustainable concrete containing GGBFS. The formulations of the compressive strength of GGBFS-C provided by COP and WCP are presented in Eqs. (22) and (23), respectively:

Fig. 6.

$$CS_{COP-SL} = \frac{(1.5\times\sqrt{S_{CE}})+(-0.4\times\sqrt{S_{SP}})+(0.2\times\sqrt[3]{3}\times S_{SL}^{2})+(1.75\times\cos(S_{CA}))}{(\sqrt[3]{4}\times 2^{S_{WA}})+(0.1\times S_{AG}^{-2})+(0.8\times\sqrt{6})}+(((-2.5\times 4^{S_{WABI}})+ \\ (0.1\times\sqrt{7}\times 2^{S_{SLBI}})+(-0.2\times\sqrt{7}\times\cot(S_{SPBI})))\times((-0.75\times S_{FATA}^{3})+(-0.5\times\exp(S_{CABI}))))^{-0.4\times\sqrt{7}} \quad (22)$$

$$CS_{WCA-SL} = (((0.4\times\sqrt[3]{4}\times\sin(S_{CE}))+(0.5\times\tan(S_{SL})))\times((0.075\times\sqrt{2}\times S_{WA})+(-0.5\times\sqrt[3]{4}\times\cos(S_{SP})))\times \\ ((0.75\times\sqrt{3}\times S_{CA})+(\sqrt{5}\times\sqrt{S_{FA}}))\times((-0.1\times\sqrt{6}\times\log_{2}^{S_{AG}})+(-0.4\times\sqrt[3]{4})))+(((-0.9\times\sqrt{6}\times 4^{S_{WABI}})+ \\ (0.6\times\sqrt[3]{4}\times\cos(S_{SLBI}))+(-0.3\times\sqrt{7}\times S_{SPBI}^{-1}))\times((0.6\times\sqrt{6}\times\cos(S_{FATA}))+(-1.8\times 2^{S_{CABI}})))^{-0.375} \quad (23)$$

where, CS_{COP-SL} and CS_{WCP-SL} are the scaled values of the compressive strength of GGBFS-C generated by COP and WCP techniques; and S_{SL} and S_{SLBI} are the scaled values of GGBFS weight and GGBFS to binder ratio, respectively.

Table 8.

4.2. Sustainability

Cement industry is responsible for generating 7% of the global anthropogenic CO_2 emissions. The concrete industry consumes enormous amounts of energy and extracts massive volumes of irreplaceable raw materials from the environment. Meanwhile, a considerable budget is allocated to the construction sector (Assi et al., 2018). Accordingly, finding sustainable solutions to protect the environment has been of immense concern to both policy makers and society. To this end, GWP, EC, MC, and cost were regarded as sustainability parameters in designing sustainable concrete mixtures. Furthermore, various concrete types, including FL-C, SF-C, and GGBFS-C, were investigated to scrutinize the effects of industrial by-products on sustainability and present the most sustainable solutions. In this section, the mixture proportions of sustainable concrete and their features are presented.

Sustainable concrete mixtures were designed for 30, 40, 50, and 60 MPa strength classes to cover the most concrete applications, according to ACI 318. The mixture proportions of the sustainable concretes are given in Table 9, which reveals that utilizing supplementary cementitious materials can reduce the content of cement in the mixture proportion, leading to the manufacture of eco-friendly concrete. Moreover, utilizing waste materials and by-products of other industries can reduce the area needed for landfills. A more detailed look at the sustainable mixtures indicates that by increasing the compressive strength, the optimal content of silica fume in mixtures steadily increased. In contrast, the weight of BFGS in the mixture designs was reduced by increasing the compressive strength, while variation in the compressive strength did not change the optimal content of fly ash.

Table 9.

The sustainability of the concrete mixtures containing SCMs was compared with the sustainability parameters of ordinary Portland cement concrete (OPC-C) mixtures presented in the experimental database to analyze the effects of the introduced sustainable mixtures on the environment and sustainable development. To this end, the mixtures of OPC-C, which exhibits 28-day compressive strengths of approximately 30, 40, 50, and 60 MPa, were selected from the experimental database. Afterwards, the average values of the sustainability parameters for the selected OPC-C mixtures were regarded as the sustainability parameters of the experimental ordinary Portland cement concrete mixtures (E-OPC-C). Consequently, these values were compared with those of the sustainable mixtures containing SCMs, which is further elucidated in the following sections.

4.2.1. Global warming potential

As previously mentioned, almost 7% of the worldwide anthropogenic CO_2 emissions is related to cement factories (Assi et al., 2018). Additionally, the global construction industry is responsible for a large portion of the total GWP produced by all industrial activities (Hong et al., 2010) and is accountable for the emission of 5.7 billion tons of CO_2, contributing to 23% of the total CO_2 emissions generated by the worldwide economic activities (Huang et al., 2018). As such, reducing the GWP, as a pertinent sustainability parameter, in the construction industry is of utmost importance to the government and environment.

The amounts of GWP emissions generated to manufacture sustainable concrete and E-OPC-C are presented in Fig. 7, which reveals that the highest quantity of GWP is relevant to E-OPC-C for all compressive strength classes. In the 30-MPa compressive strength class, the lowest amount of GWP is related to sustainable GGBFS-C, followed by sustainable FL-C, then sustainable SF-C with 54.6%, 51.1%, and 18.9% less GWP than E-OPC-C, respectively. This is due to the lower cement content in GGBFS-C mixtures as a result of the hydraulic behavior of GGBFS. However, it should be noted that the cementitious performance of GGBFS is not comparable to the Portland cement, and thus, for higher strength classes, GGBFS-C is not the mixture with the lowest GWP.

Accordingly, sustainable FL-C produced the least GWP in the 40-, 50-, and 60-MPa strength classes which can be directly related to the lower cement content in mixtures containing fly ash. This indicates that cement is the most influential parameter on the environmental impact of sustainable concrete, and therefore, reducing the cement content is the first step towards achieving more sustainable concrete mixtures. However, incorporating SCMs with hydraulic behavior such as GGBFS would help with more reduction in cement content, especially in the lower strength class (30 MPa in this study).

In the 40-MPa compressive strength class, the GWP of the sustainable FL-C, sustainable SF-C, and sustainable GGBFS-C are approximately 50.9%, 34.6%, and 33.3% less than that of E-OPC-C, respectively. Similarly, the ranking of sustainable concrete based on generating lower amounts of GWP follows a similar trend for the 50- and 60-MPa strength classes. That being said, the 50-MPa sustainable FL-C, SF-C, and GGBFS-C decreased the GWP by 44.2%, 37.2%, and 31.8%, respectively, compared to 50 MPa E-OPC-C. Moreover, substituting sustainable FL-C, SF-C, and GGBFS-C for the conventional E-OPC-C in the compressive strength class of 60 MPa roughly reduced the GWP by 35.5%, 33.6%, and 16.0%, respectively. The average GWPs of all the four compressive strength classes for the sustainable FL-C, GGBFS-C, and SF-C were approximately 44.6%, 31.9%, and 31.9% lower than that of the conventional ordinary Portland cement concrete (E-OPC-C). Hence, it can be postulated that the GWP of the sustainable concrete containing supplementary cementitious materials (fly ash, GGBFS, and silica fume) is significantly lower than that of the E-OPC-C. Furthermore, utilizing the sustainable GGBFS-C to manufacture 30-MPa concrete and fabricating sustainable FL-C with compressive strengths of 40, 50, and 60 MPa are recommended for reducing a considerable amount of GWP.

Fig. 7.

4.2.2. Energy consumption

Reducing energy consumption in the construction industry has been a significant concern (Shirzadi Javid et al., 2021). Fabricating concrete mixtures requires a vast amount of energy during the production process and preparing its ingredients. Specifically, approximately 4 GJ energy is consumed to produce one ton of Portland cement (Mehta, 2011). The construction sector was responsible for consuming 32% of the global EC in 2010, and in many developed countries, roughly 40% of the total EC is related to the construction industry (Huo et al., 2018). Therefore, reduction of EC in the concrete industry can lead to the manufacture of sustainable concretes that help to preserve the environment. To this end, the energy consumed by fabricating sustainable concrete with various compressive strengths were compared, and the results are illustrated in Fig. 8.

As Fig. 8 reveals, E-OPC-C requires the highest amount of energy for its manufacture in all the compressive strength classes. This is mainly attributed to the higher cement content in the E-OPC-C mixture. As such, it can be hypothesized that designing sustainable concrete and replacing cement with supplementary cementitious materials, including fly ash, GGBFS, and silica fume, can reduce EC since these materials require less amount of energy to be processed. By comparing the sustainable concretes and experimental ordinary Portland cement concrete in the 30 MPa-strength class, the FL-C, GGBFS-C, and SF-C sustainable concrete decreased the EC by 43.0%, 36.3%, and 21.4%, respectively. Moreover, sustainable FL-C proved to be the eco-friendliest mixture in terms of EC reduction in the 40-MPa compressive strength class. In addition, the ECs of sustainable FL-C, SF-C, and GGBFS-C were found to be 43.0%, 34.6%, and 22.9% lower than that of E-OPC-C, respectively, in the 40-MPa compressive strength class. Similarly, in the 50-MPa strength class, 39.1%, 38.5%, and 25.6% of energy can be saved if sustainable FL-C, SF-C, and GGBFS-C are substituted for E-OPC-C. Further, the 60-MPa sustainable SF-C outweighed the other mixtures in terms of lowering the EC, reducing EC by 34.5% compared to that of E-OPC-C. The main reason for requiring less EC to produce 60-MPa SF-C mixture compared to the FL-C is that silica fume needs much less energy to be processed than fly ash and since the quantity of cement is almost similar in both mixtures (370.67 kg for SF-C vs. 361.47 kg for FL-C) the influence of supplementary cementitious materials (i.e., silica fume and fly ash) is more pronounced. However, in other compressive strength classes, the cement content in FL-C mixtures is much lower than that of SF-C mixtures indicating less EC in FL-C mixtures. The sustainable FL-C and GGBFS-C can approximately save 31.3% and 13.5% of energy if they are substituted for E-OPC-C. Thus, 30-, 40-, and 50-MPa sustainable FL-C and 60-MPa sustainable SF-C prevail as the best mixtures to save energy by reducing EC among the other mixtures in the corresponding compressive strength classes.

Fig. 8.

4.2.3. Material consumption

Since huge amounts of materials are applied in the construction industry, reducing material consumption has been an immense concern (Jahanbakhsh et al., 2020). Concrete is by far the most frequently utilized man-made material around in the construction industry worldwide (Habert et al., 2011) with over 10 billion tons of concrete annually produced (Meyer, 2009). It is predicted that the annual concrete consumption will grow to roughly 18 billion tons by 2050 (Mehta, 2002). A vast amount of non-renewable materials is consumed in order to manufacture such a significant volume of concrete. Accordingly, by reducing the quantity of raw materials through using industrial waste or by-products, it is possible to save resources and, therefore, enhance the sustainability of concrete production. The amount of material consumption (MC) in preparing sustainable concrete mixtures and E-OPC-Cs is illustrated in Fig. 9.

According to Fig. 9, E-OPC-C mixtures consume the largest amount of materials in all compressive strength classes, while the performance of sustainable concrete containing SCMs is far better than that of E-OPC-C in terms of preserving materials. In the 30-MPa compressive strength class, the least MC is related to sustainable GGBFS-C, followed by sustainable FL-C, SF-C, and E-OPC-C, with consumption rates of 2084.7, 2094.5, 2245.8, and 2353.9 kg/m^3, respectively. Sustainable FL-Cs require the least amount of manufacturing material in all the 30-, 40-, 50-, and 60-MPa compressive strength classes, which could save 11.8%, 14%, and 13.8% of materials, respectively, when substituted for E-OPC-C. The lowest content of raw materials is consumed in the 30-MPa sustainable GGBFS-C, and the highest MC rate is related to 60-MPa E-OPC-C. Hence, it can be postulated that the application of supplementary cementitious material is a valuable approach to save materials and produce eco-friendly concrete. Besides, the sustainable FL-Cs and GGBFS-Cs demonstrated better performances than those of other mixtures and required the least amount of materials for their production. To obtain 30-MPa concrete, manufacturing sustainable GGBFS-C is recommended, while sustainable fly ash mixtures showed to be the eco-friendliest in terms of saving raw materials and resources in the 40-, 50-, and 60-MPa compressive strength classes.

The cement consumption of sustainable mixtures is shown in Table 9. As can be perceived, the 30 MPa sustainable GGBFS-C contains the minimum content of cement among sustainable concretes in 30 MPa class. The least amount of cement consumption is related to sustainable FL-C for 40 MPa, 50 MPa, and 60 MPa compressive strength classes. As previously stated, by reducing each kg of cement, 1.5 kg of raw materials can be saved. Therefore, it can be postulated that replacing 30 MPa sustainable GGBFS-C, 40, 50, and 60 MPa sustainable FL-C can save more raw materials through the cement reduction as well as reducing raw materials using directly in the mixture design.

Fig. 9.

4.2.4. Unit cost

Cost is an essential criteria when producing sustainable concrete, whereby reducing the unit cost of concrete is always of significant concern to both the manufacturers and end users (Shirzadi Javid et al., 2020). Fig. 10 reveals that the sustainable SF-Cs are the most expensive mixtures, and their unit cost is considerably higher than that of the other sustainable concrete and E-OPC-Cs due to the high price of silica fume. Despite this increase, silica fume in concrete mixture design has other advantages, including enhancing the compressive strength, toughness, elastic modulus, bond strength, impermeability to chloride and water penetration, resistance to chemical attacks, and abrasion resistance (Siddique, 2011; Siddique and Chahal, 2011). The unit cost of sustainable SF-C is 22.4%, 48.4%, 27.6%, and 14.9% higher than that of E-OPC-C in 30-, 40-, 50-, and 60-MPa compressive strength classes, respectively. The sustainable FL-C provides the most economical mixtures in various compressive strength classes, which is due to the lower quantity of cement in these mixtures as well as the lower price of fly ash compared to other supplementary cementitious materials. Sustainable fly ash mixtures are 36.6%, 29.2%, 38.5, and 43.6% cheaper than the conventional Portland cement mixtures. Economy-wise, the application of sustainable GGBFS-C is far more beneficial than that of E-OPC-C. In other words, the manufacturing cost of sustainable GGBFS-C is 21.1%, 15.2%, 28.2%, and 35.8% lower than that of E-OPC-C in 30-, 40-, 50-, and 60-MPa compressive strength classes, respectively. Accordingly, sustainable FL-C is the most economical concrete, followed by sustainable GGBFS-C, E-OPC-C, and sustainable SF-C.

Therefore, to enhance the sustainability through cost reduction, manufacturing sustainable FL-C proves to be the best alternative in all compressive strength classes considered in this study.

Fig. 10.

4.3. Managerial implication

In this section, the proposed concrete mixtures and E-OPC-C are compared based on their sustainability in accordance with the required 28-day compressive strength. Comparing the sustainable mixtures by the value of the objective function is not sensible because the cost and environmental objective functions of different concrete types are scaled depending on their corresponding range of cost and environmental impacts, as indicated in Table 5. To address this issue, gray relational analysis (GRA) was performed to prioritize all mixtures and introduce the most sustainable mixture in each compressive strength class. The primary aim of GRA is to optimize the multi-responses as they are converted to a single grade and then compare the various alternatives by the specified grade (Ghavami et al., 2021). By virtue of GRA, the sustainability of the mixture proportions was scrutinized and then compared. In other words, the effects of cost, GWP, EC, and MC, as process parameters, were integrated by GRA, and the grey relational grade (GRG) of the mixtures were obtained for ranking. The maximum value of GRG is equal to 1, which is associated with solutions that possess the highest level for all process parameters (Naseri et al., 2021a). Hence, increasing GRG increases the sustainability of the examined concrete. The GRGs of the mixtures and their rankings according to sustainability (GRG scores) are given in Table 10.

Based on the GRA results, by increasing the 28-day compressive strength among all concrete classes, the GRG values of the studied concrete mixtures decreased, indicating that the concrete production with higher 28-day compressive strength causes more detrimental environmental impacts than the concrete with lower strength. Furthermore, the results in Table 10 demonstrate that the fly ash provides the highest level of sustainability among the sustainable mixtures. In all compressive strength classes, the most sustainable mixtures are associated with sustainable FL-C followed by GGBFS-C, SF-C, then E-OPC-C. Moreover, sustainable SF-C outweighs E-OPC-C in the 30-, 50-, and 60-MPa compressive strength classes in terms of sustainability. Accordingly, it can be deduced that the sustainability of the concrete mixtures introduced in this study is significantly greater than that of the conventional Portland cement presented in other studies. Overall, manufacturing sustainable FL-C appears to be the best alternative to enhance the sustainability of concrete.

Table 10.

5. Conclusions

In this study, the mixture designs of sustainable and eco-friendly concrete containing supplementary cementitious materials, including fly ash, silica fume, and ground granulated blast furnace slag, is estimated. To this end, a novel machine learning method called coyote optimization programming was developed and introduced to predict the compressive strength of the aforementioned concrete types. The precision of the presented method was compared with the accuracy of conventional machine learning techniques, including water cycle programming and deep learning. The results indicate that the proposed coyote optimization programming is the most accurate method to estimate the compressive strengths of concrete. Meanwhile, the introduced machine learning technique is capable of generating the equation for the compressive strength of concrete based on its mixture proportion.

Herein, considering the unit cost and environmental impacts, including GWP, EC, and MC, as sustainability parameters, the sustainable concrete designs exhibit various compressive strengths of 30-60 MPa. Afterwards, the designed sustainable mixtures were compared with conventional ordinary Portland cement concrete in terms of these parameters. The results indicate that the 30-MPa sustainable GGBFS-C, 40-MPa sustainable FL-C, 50-MPa sustainable FL-C, and 60-MPa sustainable FL-C are more eco-friendly in the corresponding compressive strength classes and reduce GWP emissions by 54.6%, 50.9%, 44.2%, and 35.5%, respectively, compared to Portland concrete.

Moreover, the 30-, 40-, and 50-MPa sustainable FL-C designs provide the lowest amount of EC with reductions by 43.0%, 43.0%, and 39.1%, respectively, compared to conventional ordinary Portland cement concrete (E-OPC-C). In the 60 MPa compressive strength class, the highest energy savings was exhibited by the sustainable SF-C, which reduced EC by 34.5% compared with the Portland concrete.

Based on the MC analysis, the least amount of raw materials is required for manufacturing the 30-MPa sustainable GGBFS, which can reduce MC by 11.4%. Furthermore, the eco-friendliest mixtures in terms of MC correspond to the 40-, 50-, and 60-MPa sustainable FL-C. As compared with the 40-, 50-, and 60-MPa ordinary Portland concrete (E-OPC-C), the 40-, 50-, and 60-MPa sustainable FL-C decreased MC by 280.2, 339.5, and 337.0 kg/m^3 and required 11.8%, 14%, and 13.8% less raw materials, respectively.

According to the results of cost analysis, sustainable FL-C is the most economical mixture in all the compressive strength classes, followed by sustainable GGBFS-C and SF-C. Compared with E-OPC-C, the 30-, 40-, 50-, and 60-MPa sustainable FL-C can reduce the concrete unit cost by 34.7% 25.7%, 36.7%, and 43.7%, respectively.

Based on the gray relational analysis, 30-MPa sustainable FL-C is the most sustainable mixture, followed by 30-MPa sustainable GGBFS-C, 40-MPa sustainable FL-C, 50 -Pa sustainable FL-C, and 40-MPa sustainable GGBFS-C with GRG scores of 1.000, 0.898, 0.854, 0.749, and 0.681, respectively. In addition, FL-C provides the highest level of sustainability in all compressive strength classes, while 30-MPa sustainable FL-C reduces the unit cost, GWP, EC, and MC by 36.6%, 51.1%, 43.0%, and 11.0%, respectively.

6. Limitations and recommendations for future studies

One of the limitations of this study is to consider an individual concrete's characteristic, compressive strength, to optimize mixture design. That is, some other characteristics, such as durability indicators, workability, and rheological properties, are excluded from this study. Hence, it is recommended that the mentioned characteristics are considered in future studies, and the results of the proposed models are compared with the current study outcomes.

This study considers three environmental parameters, including global warming potential emission, energy consumption, and material consumption. It is suggested that other environmental parameters, such as non-hazardous waste disposed, hazardous waste disposed, and radioactive waste disposed, will be considered in future studies.

Data Availability Statement

The data that support the findings of this study, including the mixture design of different concrete types, are available on request from the corresponding author.

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