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Machine learning predictions for optimal cement content in sustainable concrete constructions

Mohammadsadegh Shahrokhishahraki [a], Mohammadhossein Malekpour [b], Sajjad Mirvalad [a], Gloria Faraone [c,*]

[a] School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran
[b] Department of Computer Engineering and Software Engineering, Polytechnique Montreal, Canada
[c] Department of Civil, Construction, and Environmental Engineering, San Diego State University, USA

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ABSTRACT

The designated concrete compressive strength at 28 days plays an important role in determining the quantity of cement (water to cement ratio) needed in concrete mix designs. Whilst a 28-day target is common, some structural elements receive deferred loads during construction, allowing a reduced cement content and the possibility to optimize the concrete mix to target full strength at 90 days. Machine learning techniques are used in this study to optimize the concrete mix design of structural elements that commonly receive deferred loads, e.g., foundation and pavements, targeting a 90-day full strength. Specifically, the compressive strength of concrete samples cured for 28 and 90 days are considered to estimate the cement content per m^3 of concrete using Artificial Neural Network and Regression algorithms. The proposed machine learning and deep learning methods are proved to be capable of predicting the cement content with 94% and 90% accuracy, respectively. The Elastic Net algorithm shows the best performance in cement content optimization to a target 90-days compressive strength. This algorithm is hence employed to assess the carbon reduction benefits in a real case study: a typical mid-sized reinforced concrete structure is considered as a baseline to quantify the environmental benefit of optimizing the cement content for a 90-days target compressive strength. Results of the case study show that the proposed method may result in a reduction of approximately 10% in cement usage, consequently leading to a parallel reduction of about 10% in carbon emissions.

1. Introduction

The effects of climate change on the environment have become more severe in the recent years, raising the need to globally reduce carbon emissions and mitigate their negative consequences on our planet [1–8]. According to the Environmental Protection Agency (EPA), more than 20% of global greenhouse gas (GHG) emissions in 2021 came from the industrial sector [9], amongst which the cement industry is the third largest energy consumer, with approximately 7% of global GHG emissions [10]. As a reference, the total GHG emissions by the cement industry were roughly 1.50 Gt CO_2 in 2018 [11], with a large participation of concrete production processes requiring carbonate decomposition, fuel combustion, and electricity usage [12]. With an estimated 10 Bt production, concrete is indeed one of the most used cement-based construction products due to its accessibility and affordability, as well as favorable mechanical, thermal and insulation properties, often superior to other conventional construction materials (e.g., steel and wood)

* Corresponding author.
E-mail address: gfaraone@sdsu.edu (G. Faraone).

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[13–15]. However, the environmental impact of extensive concrete usage cannot be overseen. Statistics show that the United States alone consume over a hundred million metric tons of cement for concrete production, leading to an approximate one-to-one ratio of carbon dioxide emissions per pound of produced cement and contributing to more than a hundred million metric tons of GHG emissions [16–18].

As the need for new residential and commercial concrete buildings, bridges, tunnels, and other infrastructure is expected to increase due to population growth, the demand for concrete and the negative effects related to its usage and production are also projected to increase. Therefore, there is an urgent need to significantly reduce and/or optimize the use of concrete and other cement-based construction materials to mitigate GHG emissions by using new methods and alternative products that will concomitantly satisfy industrial needs, keep a competitive production cost, and reduce the environmental impact. A strong research activity trying to address this problem has emerged over the last decade (2014–2023), with more than 840 publications discussing advancements, roadblocks and alternatives to the development of environmentally sustainable concrete [15,19–21], and highlighting possible solutions and knowledge gaps in the field. Drawing from this, a novel method is proposed in this paper that may be adopted by designers and constructors to address the challenge of reducing CO_2 emissions in concrete production, while considering ease of implementation and applicability. Using machine learning tools, the method proposed herein aims at optimizing the cement content to target a full compressive strength at 90 days, hence reducing carbon emissions.

The structure of this article is as follows: Section 2 provides background information on the identified barriers in predicting compressive strength at a longer target time and the application of machine learning to overcome these obstacles. Section 3 discusses the methodology employed in this study, including the algorithms used to develop a tailored machine learning model targeting 90-day compressive strength. In section 4, the results of the machine learning model are presented and compared to find the best approach based on the available data. The proposed model is then applied to a case study, i.e., the design of a medium size reinforced concrete building, to estimate the carbon reduction associated with a 90-days concrete compressive strength. Results of the case study in terms of estimated GHG emissions are presented to assess the carbon reduction potentials of the alternative approach proposed in this research. The case study serves as a mean to emphasize the environmental benefits of this research moving towards sustainable construction.

2. Background

2.1. Approaches to reduce carbon emissions

The decarbonization of cement may involve improving energy efficiency, switching fuel, implementing Carbon Capture Utilization and Storage (CCUS), and reducing the clinker to cement ratio [22]. The literature shows different approaches that targeted different stages of concrete production, from the material selection to the mix design optimization. Specifically for concrete production, new methods to improve material and construction efficiency and new types of concrete to absorb the CO_2 emissions were considered [23]. As an example [24,25], replaced cement with alternative materials, e.g., fly ash, slag sand, and stone powder, to reduce the GHG emissions related to concrete production, while also reducing industrial waste. In fact, using supplementary cementitious materials like recycled aggregates, fiber scraps and furnace slag, which are byproducts of other production processes, would minimally contribute to additional carbon dioxide emissions [26,27]. However, it is here noted that these materials are often not always accessible nor available, complicating the real-life implementation of these solutions [28]. In some cases, a longer curing time is required for the hydration of cement due to the lower reactivity of novel cement, which can cause drastic changes in the construction timeline and can even affect the design procedure [29–32]. The higher cost related to the collection and processing of the byproducts and technical and regulatory barriers may slow down a large-scale adoption of the proposed alternative binders. Adding to these, there is still limited demand for low carbon products in the industrial sector due to the lack of effective energy global policies [29,33–35]. The development of new technologies, indeed, requires a higher level of support for testing and upscaling, which is not provided at the current time [36], hence the construction industry still favors conventional materials to limit costs related to innovation [37,38]. Lastly, it is recognized that the insufficient awareness within society about the environmental impact of cement production on climate change may lead to a lower emphasis on efforts to reduce emissions [39].

Considering these obstacles, the optimization of existing methods appears as a valuable and fast alternative to the modernization of traditional techniques to reduce the carbon footprint of concrete. Leveraging innovative machine learning and deep learning tools, this study focuses on the optimization of the material proportions in concrete mixture, predicting the necessary cement content based on the 90-day compressive strength instead of the conventional 28-day target. This method results in a reduced use of Portland cement in concrete mixtures, thereby contributing to the sustainable development of the construction industry.

2.2. 90-Day compressive strength approach

Adapting the mechanical characteristics of concrete to meet the needs of construction timelines has been the focus of recent research [40]. However, most of these studies focus on speeding up the curing process to meet time constraints [41–44]. As an example, a novel technique named microwave heating has gained much popularity amongst researchers for accelerating curing process of concrete as a new method or coupled with other methods [45–53]. However, the design and construction of suitable microwave systems is still challenging and would involve significant changes in the industry process [45].

An alternative approach to reduce carbon emissions while minimizing disruptions in the construction industry is here identified in optimizing the concrete mix design to target a 90-days compressive strength. Whilst the construction timeline for buildings depends on various factors such as area, number of stories, and architectural plans, a conventional timeline for each floor according to ACI 318-19 [54] is approximately 15 days, half of which is for curing columns and the other half for curing beams and slabs. Hence, for a building with six stories or higher the construction estimation timeline will exceed the 90-day limit for the concrete footing to reach the nominal strength and targeting design strength at 90 days will result in a safe and environmentally conscious choice. It is estimated that for multi-story buildings, the total and final set of loads will not be applied on the footing in a short period after pouring, and concrete compressive strength will increase during this time window depending on concrete mixture properties, environmental conditions, and curing method [55]. Therefore, multi-story reinforced concrete buildings usually allow more than 90 days after the concrete footing pour to gain concrete compressive strength, before the construction is ultimately completed. For multi-story buildings with mat footings, as well as road construction with concrete pavements, bridge construction with concrete piers, a 90-days target strength may be reasonably assumed to limit carbon emissions.

2.3. Machine learning and concrete strength modeling

In the past decade, researchers have been challenged with the task of modelling the properties of innovative concrete mixes containing alternative materials, e.g., recycled aggregate, fiber scrap aggregate, silica fume, furnace slag and, fly ash [26,27,56–58]. Since simple linear regression is not suitable to describe the complexity of different alternative materials [59], innovative algorithms, like the Artificial Neural Network (ANN) and support vector machine (SVM) are adopted [60]. Previous research shows that an ANN approach is suitable for estimating the compressive strength of ordinary and high-performance concrete with pozzolans. Yeh [61] optimized the concrete mix proportions for desirable workability and compressive strength by combining non-linear programming and ANN. Feed-forward neural networks with multiple layers were used to predict the 28-day compressive strength of concrete [62]. Prediction of the concrete strength by using the physical features of a specimen and proportions of the concrete mixtures alongside the environmental conditions was done by Gupta et al. [63]. The relationship between concrete slump and other components was explored by Yeh [64] and resulted in a demonstration of the capability of ANN for modeling nonlinear relationships such as predicting the slump of highly complex materials. Another attempt to predict the 28-day strength of concrete using ANN was made by Ozturan et al. [65], however, the dataset in this research included only low and medium concrete strength values. Structural lightweight concrete compressive strength prediction was explored by Alshihri et al. [66] who were able to predict the compressive strength at the age of 3, 7, 14, and 28 days successfully. Aggarwal [67] developed a model to predict the 28-day compressive strength of self-compacting concrete with bottom ash that used literature and experimental data for training the ANN [68].

Although the literature shows remarkable success in modeling the mechanical properties of concrete, translating these efforts into practical applications in real-world construction projects is often challenged by the complexity of machine learning or hybrid models and engineering guidelines and standards [69]. Minimizing the disruption, Regression models and ANN are used in this study to predict the optimal cement content for the concrete mixture to reach the nominal compressive strength in 90 days instead of 28 days. Because the dataset for this study does not contain alternative materials, the complexity of the relationship between the components is not as complex as in the literature, so regression models are expected to have high accuracy. Different regression algorithms are developed to find the best predictions and offer a relatively simple tool to reduce carbon emissions and address one of the most critical challenges of the 21st century.

3. Methodology

In this section, the methodology used to determine the concrete mixture for targeting the 90-day compressive strength is presented in detail. First, the dataset used in this research is described to understand the available features and their distribution. All the different algorithms are then briefly presented to clarify the approach of the methodology.

3.1. Data description and feature selection

In this research, 261 different batches of concrete were cured in fresh water and tested at 7, 28, and 90 days to determine the compressive strength of concrete by conducting a compression test on standard cylindrical specimens. Two, three, and one sample are used to determine the 7-day, 28-day, and 90-day compressive strength of concrete, respectively and the correspondent average values indicate the compressive strength at these ages. For each batch of concrete, the concrete slump test is also conducted, and the results reported. The mix proportions of each concrete batch are thus characterized by eight properties, namely the 28-day compressive strength, 90-day compressive strength, concrete slump test, nominal maximum aggregate size, water content, cement content, coarse aggregate content, and fine aggregate content. Table 1 shows the statistical parameters for the dataset. The 90-day compressive strength value ranges from 26.7 to 55.0 MPa, indicating a low to medium compressive strength of the experimental concrete batches.

Table 1
Statistical parameters for the concrete [1 mm = 0.039 in; 1 kN = 0.225 kip].

Attribute	Unit	Min	Max	Average	Standard deviation
Cement	kg/m^3	273	489	364.38	47.10
90-day compressive strength (CS)	MPa	26.7	55.0	38.00	5.12
Slump test	cm	7	20	12	2.34
Nominal maximum size of aggregates	mm	19	50	37.11	6.51
Water	kg/m^3	166	216	182.52	7.94
Coarse aggregate	kg/m^3	992	1184	1131.71	31.49
Fine aggregate	kg/m^3	607	790	711.53	40.49

There are several factors in concrete placement and curing that could significantly affect the compressive strength of concrete, hence, there are different compressive strength gains reported for similar mix designs. In this research, the correlation between 28-day and 90-day compressive strength is further investigated to filter the dataset and eliminate noise in the data. Therefore, only the samples whose 90-day compressive strength is between 1.1 and 1.25 times the one at 28 days are used in the model development and the remaining data is removed from the dataset. The 1.1 lower limit is set to exclude those specimens which did not gain more than 10% compressive strength during curing, noting that if a concrete batch cannot gain more than 10%, there is a high probability that the curing or the concrete placement faced some problems that halted the hydration process [70]. The upper limit is set to limit the compressive strength gain and avoid forcing the development of low-cement concrete that inevitably needs other adjustments, e.g., additives and/or expensive curing methods, to reach the target strength [71]. These adjustments would indeed contradict the main goal of this paper, which is reducing carbon emissions in an easy and effective way. Hence, limiting the compressive strength in the data selection phase ensures conservative model predictions and reduces possible model overestimations.

As a result of the filtering process and noise reduction, a final dataset of 112 samples is considered in the study. This dataset is further subdivided into training and test datasets to develop the Regression and ANN models. The histogram of the dataset is shown in Fig. 1 for each feature considered in this study. A good distribution for the 90-compressive strength, concrete slump test and required cement content is observed in Fig. 1, whereas less scatter is observed for the nominal maximum size, coarse aggregate and mixing water content.

3.2. Machine learning and deep learning methods

Whilst previous studies used the cement, water, coarse aggregates, and fine aggregates content as inputs data to predict the compressive strength of Ordinary Portland Cement (OPC) concrete with machine learning [72–75], the fine aggregates cannot be considered as input data in this study. The fine aggregate's content depends, indeed, on the cement content in both the mass and absolute volume basis methods, as for ACI guidelines [76]. Since the fine aggregate content is calculated with the cement content, this linear correlation overshadows the correlation between other input features and cement content, and the machine learning model cannot handle new data [76]. Hence, the input data for both the regression and ANN models are the nominal 90-day compressive strength, the concrete slump test, the nominal maximum size of aggregates, the coarse aggregate, and the mixing water content.

Following the conventional approach of train-test split to reduce the overfitting problem, the dataset is split into a train set (70% of the total dataset), a test set (15% of the total dataset), and a validation set (15% of the total dataset). The training dataset is used as a data sample that allows the machine learning model to find the correlations between the input and output parameters. During the training process, the model performance is validated with a validation set, which is a separate dataset that the model hasn't been trained on to tune the model's hyperparameters. Lastly, a dataset is saved to determine the performance of the trained model based on a dataset that has not been presented to the model beforehand.

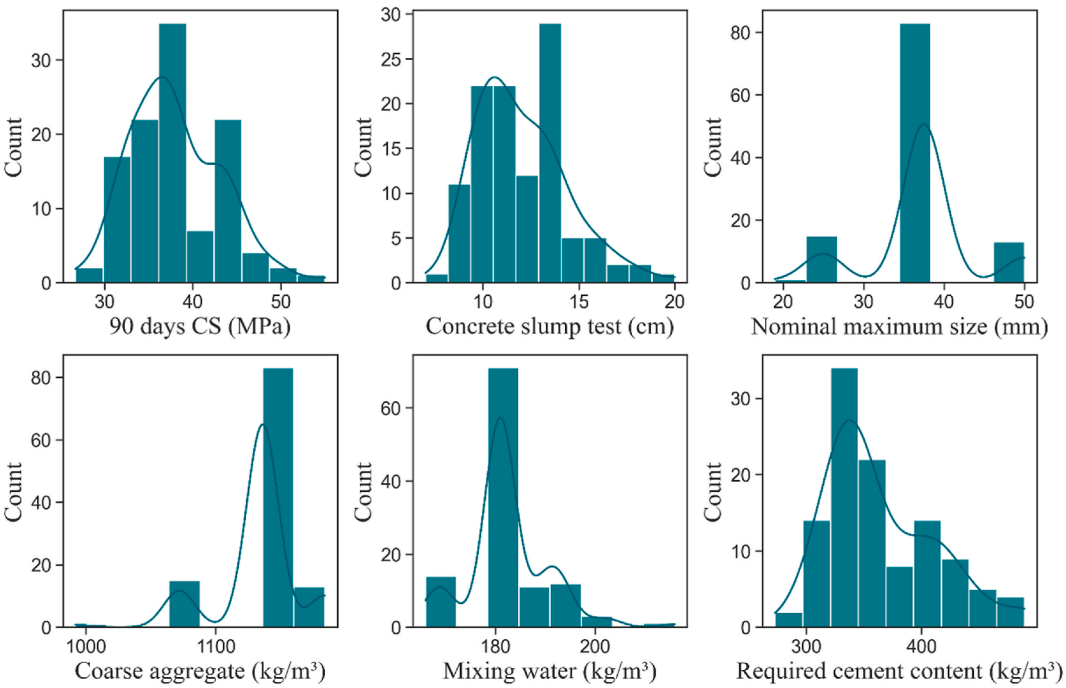

Fig. 1. Histograms of the parameters considered in this study.

In this research, four different regressor models, namely Decision Tree regressor, Elastic Net, Extra Trees Regressor, and Random Forest Regressor from the scikit-learn [77] library are considered in the search of the best-fitting algorithm to the considered dataset. A brief introduction for each algorithm is presented below.

3.2.1. Decision Tree Regressor

The Decision Tree algorithm is used for both classification and regression problems [78]. In some problems where linear regression falls shorts on achieving high accuracy, the Decision Tree may be an excellent alternative. Specifically, by using tree leaves to develop regression models, the predictions can be a class label or a continuous value depending on the nature of the problem [79].

3.2.2. Random Forest Regressor

Breiman [80] proposed the Random Forest algorithm as an extension of the classification and regression tree algorithms to convert a complex problem into several, less complicated problems. The proposed algorithm creates an ensemble of decision trees by using Bagging algorithms, which construct different data examples, i.e., bootstrap, and train the decision trees to estimate the output. The final prediction is the average of all the outputs received from the train decision trees [81,82]. This algorithm can improve the prediction accuracy and reduce overfitting error.

3.2.3. Extra Trees Regressor

The Extra Trees algorithm, an extension of the Random Forest algorithm, uses all the training samples to train the prediction trees, while the latter only implements bootstrap for the training process. In addition, in contrast to Random Forest, which uses a greedy algorithm to find the best split node, the Extra Trees algorithm randomly chooses the split points of the decision tree [83,84].

3.2.4. Elastic Net

The Elastic Net algorithm is a regularized linear regression that combines two penalty functions to find the best predictions. The ratio of the two penalty functions can be tuned in the Scikit-learn package with a parameter in the range of [0,1]. This is formulated such that the higher the parameter, the closer the algorithm is to the least absolute shrinkage and selection operator (lasso) [77,85]. This is a regression method specifically developed to reduce the model complexity and prevent the over-fitting typically resulting from simple linear regression.

3.2.5. Deep Learning Approach – Artificial Neural Network

ANN is one of the most powerful tools to make accurate predictions of the behaviour of complex systems [86]. In neural networks, the relationship between the components of an artificial structure is determined by modifying the weight of each connection [87]. In general, a neural network includes an input layer that has the same number of neurons as the number of input features, one or multiple hidden layers, and one or multiple neurons in the last layer, which depends on the number of outputs. Each neuron in the hidden layers carries the information and weight of the connection and passes it to the next layer. The most important part of training a neural network is to reduce the error during training. As the number of hidden layers and neurons in each layer changes, the error and the training process will improve. However, as the number of neurons increases, the process of training will be more time consuming. Hence, it is important to find the optimum combination of neurons and hidden layers to reach an acceptable result in a short time. The following sections describe the procedure used in this study to optimize the model.

The ANN used in this research is based on the TensorFlow library in Python. The model has five neurons in the input layer, one neuron for each feature, one hidden layer with 16 neurons, and an output layer with one neuron. Optimizing the number of neurons is done by trial and error and the network with the least mean squared error (MSE) is chosen. The number of neurons varies in the range of 1 and 30 and the MSE is calculated while other parameters of the model are kept constant. The results in Fig. 2 show that the MSE reduces as the number of neurons increase. The results of training process are instead presented in the results section.

4. Results and discussions

4.1. Regression models

The results of the regression models developed in section 3.2 are presented in Table 2. The Elastic Net algorithm shows the highest test accuracy, hence the best performance, and is selected for further tuning. The tree-based algorithms, instead, show a substantial gap between train accuracy and test accuracy, i.e., they are susceptible to overfitting to a high degree, see Table 2.

To provide a better insight into the algorithms' performance, the predictions and real values of all the samples are presented in Figs. 3–6. The tree-based algorithms match the actual values of most of the data set, but their performance drastically changes when the models are presented with new data outside of the training set.

To further improve the performance, the Elastic Net [77,88] parameters are tuned by running the model with different values for each of the parameters. The best results occur with the following parameters: 'l1_ratio' = 0.5, 'max_iter' = 1000, 'normalize' = False, and 'tol' = 0.001. Finally, the Elastic Net is trained with the best parameters to find the R^2 score, which resulted to be approximately 0.94. The Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) for the training, testing, and full dataset are also calculated and presented in Table 3. The comparison between the Elastic Net predictions and the actual values from the dataset in Fig. 7 shows good overall agreement between the actual and predicted cement content at 90 days.

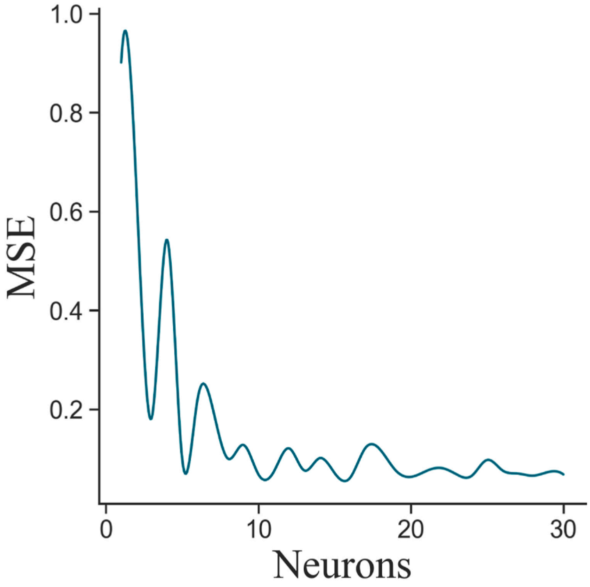

Fig. 2. MSE error indicator for different networks.

Table 2
Results of regression models accuracy and time consumption.

	Algorithm's Name	Train Accuracy Mean	Test Accuracy Mean
1	Elastic Net	0.912	0.908
2	Random Forest Regressor	0.971	0.848
3	Extra Trees Regressor	0.989	0.820
4	Decision Tree Regressor	0.989	0.766

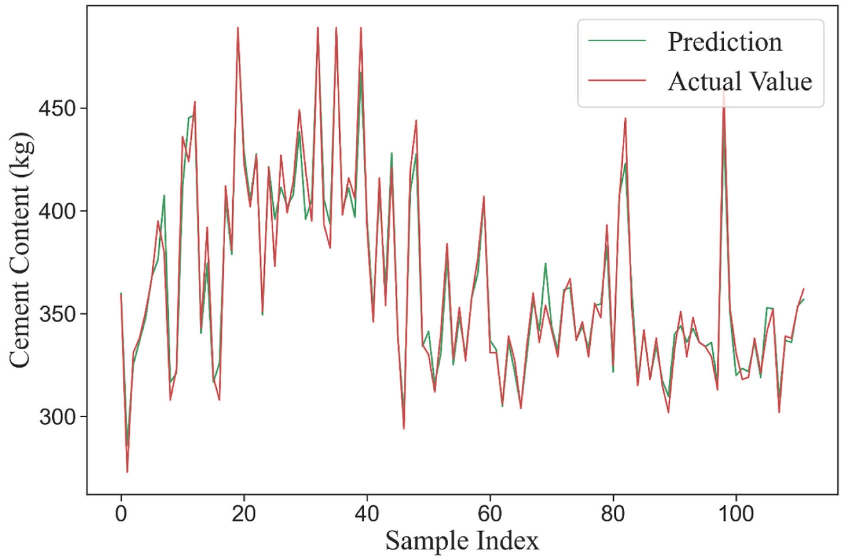

Fig. 3. Random Forest performance.

4.2. Deep learning model

The predictions for the ANN model are not as close as the regression model, especially for areas where less data is available (90-day compressive strength ≤30 MPa). The dataset size in this research is not large enough to support a complicated neural network algorithm and as a result, there is not enough data for train, validation, and test dataset. This caused underfitting issues in different neural networks, as it can be seen in Fig. 8.

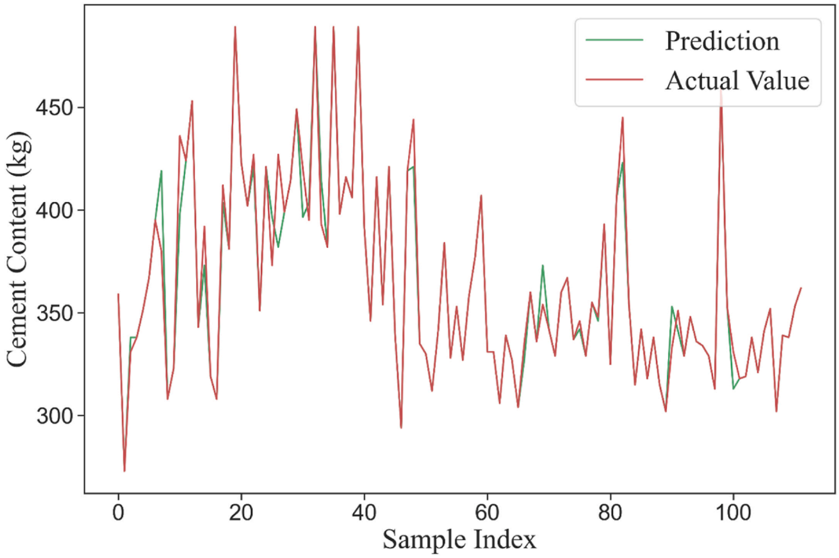

Fig. 4. Decision Tree performance.

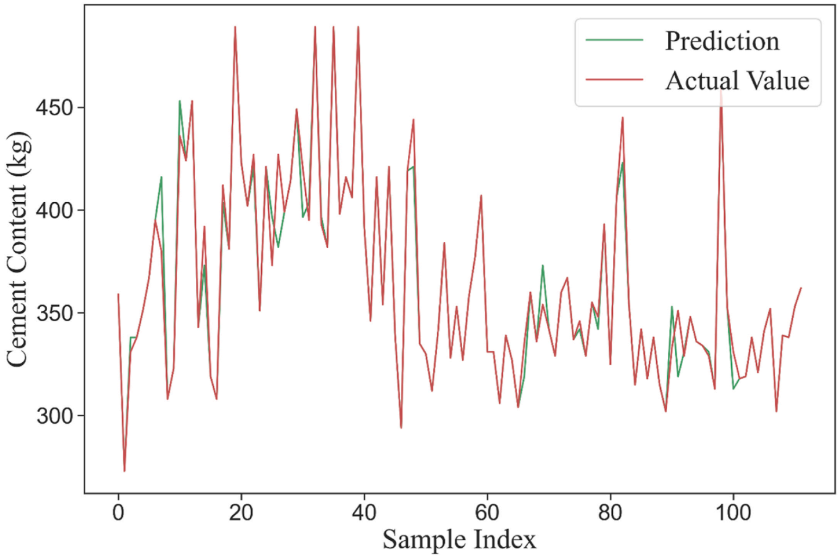

Fig. 5. Extra Trees performance.

Results of the ANN and regression models indicate that the dataset features in this research are insufficient to generalize the data for a wide range of compressive strength with the considered models. It is also observed that high accuracy predictions are reached in the 30–45 MPa range, having more data available within this range to train the considered models. In addition, it is noted that for concrete strength values larger than 45 MPa, other features are needed to predict the cement content. For example, to produce concrete with high strength and performance, only increasing the cement content will not suffice and pozzolans or supplementary cementitious materials are required in the mix. Furthermore, as can be seen in Figs. 7 and 8, the predictions have a marked linear relationship sometimes in disagreement with the actual values in the 30–45 MPa range. This indicates that relations between 90-day compressive strength and cement content have not been fully discovered and require further investigations.

For future research on predicting the cement content, more data is needed with 28-day compressive strength of 20–25 MPa so that the 90-day compressive strength will reach 25–30 MPa. In addition, the effects of using different admixtures and superplasticizers needs to be examined. Also, to generalize the results of the model, some qualitative, quantitative and environmental features, e.g., the curing method, the concrete placement, the pouring temperature, and the air humidity, may be included to increase the accuracy of ANN.

It is noted that the dataset considered in this research is limited in size, affecting the comprehensive understanding of the ANN and the simpler regression models. However, considering that finding a dataset that contains both 90-day and 28-day compressive strength of concrete for the mixture is a challenging task, the dataset used in this research is considered to be sufficient for a prelimi-

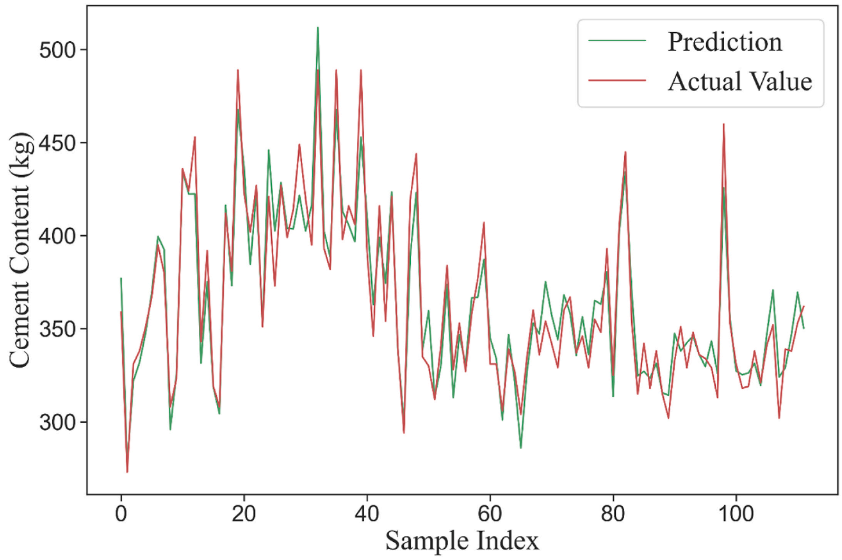

Fig. 6. Elastic Net performance.

Table 3
Comparison of different errors for dataset.

Dataset	RMSE	MAPE
Train data	11.0483	0.0269
Test data	14.2492	0.0309
All data	13.8112	0.0303

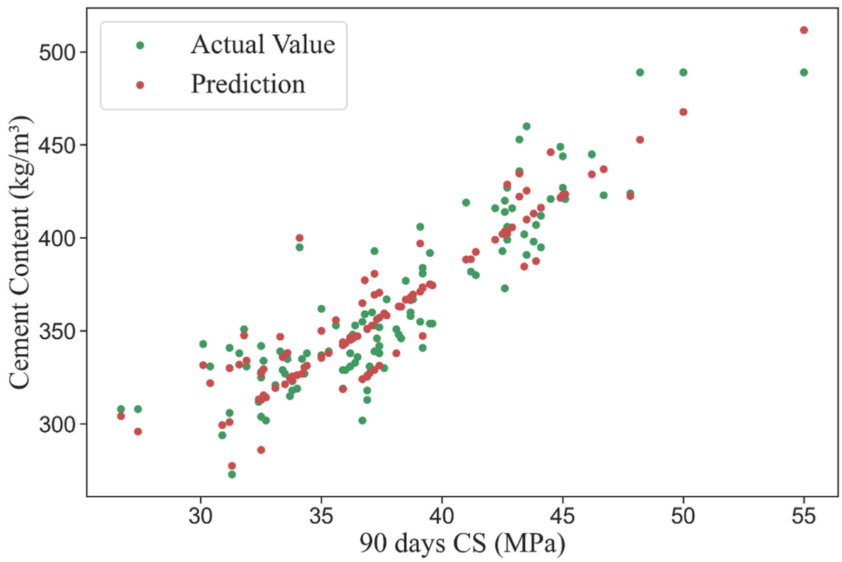

Fig. 7. Comparison of predictions and actual values for Elastic Net.

nary understanding of the proposed method. This is particularly significant given that this research represents one of the pioneering efforts in implementing such an approach, and pertinent data from literature reviews are scarce to this date.

Comparing the available literature on predicting concrete compressive strength, earlier publications faced similar constraints with limited data for model development. Sample sizes in these studies ranged from 27 to 240, indicating a consistent challenge in obtaining substantial datasets [89–95]. The average sample size employed in the literature aligns with the data utilized in this study. Notably, the evolution of research on compressive strength prediction, shows increasing sample sizes up to 1030 and 482 data in recent years, reflecting the potential for future updates of the current study [96,97]. With the accumulation of publications in this area, more

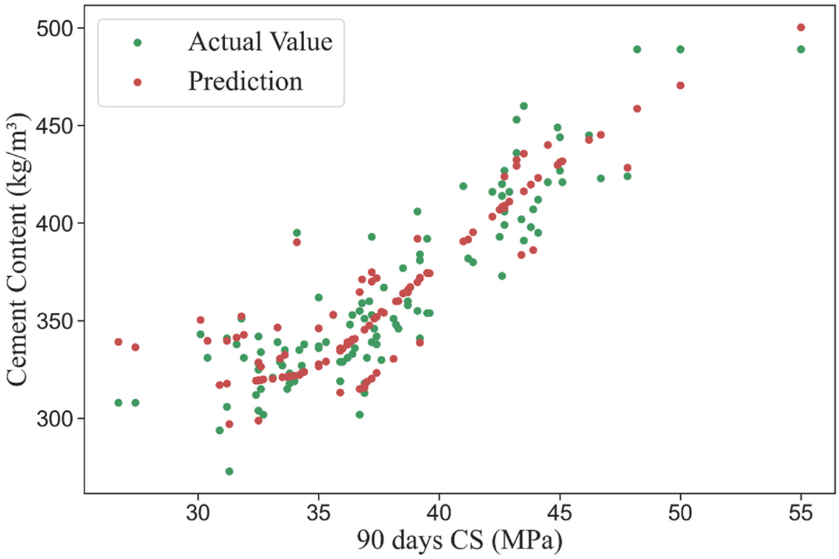

Fig. 8. Comparison of the predictions and actual values for ANN.

expansive studies, will benefit from larger sample sizes, similar to those witnessed in the advancement of compressive strength prediction methodologies over time.

5. Application of the proposed model to a case study

The models developed in this study to optimize the concrete mix are applied to a case study and the results are compared in the following sections. The case study considered for validation is a typical 6-story office building located at the Iran University of Science and Technology in Tehran. The considered building is a technology research centre, built for the School of Mechanical Engineering approximately 10 years ago. For this case study, only the footing is considered to reach its nominal compressive strength in 90 days, receiving full design loads in a longer time frame with respect to the other structural elements. This type of footing (i.e., mat footing) is chosen as a case study because it is commonly used in large and mid-sized trade centres and office buildings. Also, the volume of concrete in these buildings is larger than a typical residential building, so the CO_2 emission and cost reductions may be significant.

The case-study building has a mat footing with an area of approximately 4000 m^2. The geometry of the plan is rectangular, and the total volume of concrete used in this footing is 4365 m^3, with 70 kg/m^3 of steel reinforcement. The concrete compressive strength is measured to be 30 MPa and a 10-cm slump is recorded.

To calculate the CO_2 emissions of the standard 28-day compressive strength concrete and 90-day compressive strength concrete proposed in this research, Athena Impact Estimator for Building (AIEB) is used. The AIEB is a free software for evaluating whole buildings and assemblies based on the established life cycle assessment (LCA) methodology. Because this case study only includes the foundation and footing, only the foundation assembly is created in the software. The estimated cost of raw materials (concrete and steel reinforcement) reflects the actual geometry and detailing of the foundation in the case study.

Two foundation assemblies (i.e., “as built”, and with the optimized concrete mix) are added to two different projects with the same geometry and amount of reinforcement. The two mix designs are defined in the software using the “User Defined Concrete Mix Design Library” option in the toolbar.

The “as built” concrete mix is calculated using ACI 211.1-91 [76]. The calculated proportions, summarized in Table 4, are the starting point for the trial-and-error procedure in the laboratory. It is worth mentioning that the nominal maximum size of the aggregates depends on the manufacturer and the raw material available at the concrete plant. The coarse aggregate content is a function of the nominal maximum size of aggregate; hence these features will remain the same for both 28-day and 90-day compressive strength alongside the nominal compressive strength and fresh concrete slump.

The new optimized concrete mixture instead includes coarse aggregate (68% crushed stone and 32% natural coarse aggregate, following the software default mix design) and fine aggregate (88% natural and 12% crushed stone, following the software default mix design). Since only the nominal compressive strength, nominal slump test, and nominal maximum size of concrete are available from design reports of the case study, the other inputs must be calculated using ACI 211.1 [76]. The process of determining the mix design proportions includes the following steps:

Table 4
Concrete mix design based on 28-day compressive strength [1 mm = 0.039 in; 1 kN = 0.225 kip; 1 kg = 2.205 lbs.].

Nominal Compressive Strength	Concrete Slump	Nominal Maximum Size of Aggregate	Mixing Water	Cement Content	Coarse Aggregate	Fine Aggregate
30 MPa	10 cm	37.5 mm	181 kg	329 kg	1136 kg	741 kg

1. Determine mixing water based on nominal maximum aggregate size.
2. Determine the coarse aggregates amount based on the fineness modulus and the nominal maximum size of aggregate.
3. Predict the cement content, using the developed model proposed in this paper.
4. Determine the fine aggregates content based on the absolute volume method.

These proportions are designed to reach the nominal compressive strength in 90 days instead of 28 days using the Elastic Net model for its good prediction accuracy, especially in the range of 30 MPa maximum strength. To meet the structural design requirements, the mechanical properties of the concrete in the optimized mix are kept the same as the "as built" mix. However, the cement content of concrete is reduced and replaced by the new cement content predicted using the machine learning algorithm presented in this research. The result of the prediction for cement content by Elastic Net is shown in Table 5.

Compared to the "as built" mixture in Table 4, a larger fine aggregate content is included in the optimized concrete mixture to compensate for the reduction of cement content. It is noted that the total volume of the optimized concrete mix is the same as for the "as built" mixture.

AIEB calculates the LCA measures in 5 stages: product, construction process, use, end of life, and beyond building life. The results presented in Tables 6 and 7 indicate a 170-tonne reduction in CO_2 emission (8% reduction) for a 4300 m^3 mat footing when considering 28-day versus 90-day concrete compressive strength. This aligns with the literature, estimating that each tonne of ordinary Portland cement generates between 0.73 and 0.85 tonnes of CO_2 emissions [98,99]. Hence, focusing only on the production stage could result in savings of approximately 131 tonnes of CO_2 emission, assuming an average emission of 0.79 tonnes per tonne of cement.

It is noted that the results in Tables 6 and 7 slightly exceed this average estimated emission value, as they include additional factors such as transportation, construction and installation processes, de-construction, demolition, waste disposal processing, and activities beyond the building's lifecycle. In addition, it is observed that the use of a 90-day concrete also leads to a substantial reduction in fossil fuel consumption, total primary energy usage, and non-renewable energy resources.

In the case study presented herein, the optimal cement content targeting 90-days strength is found to be about 10% lower than the conventional cement content required for concrete to achieve its nominal compressive strength at 28 days. This can lead to about 10% reduction in carbon emissions, as validated by the LCA conducted in this section. While the total amount of carbon savings are project-specific and cannot be generalized, this case study serves as a practical demonstration that carbon reduction of at least 10% is achievable. This outcome holds great promise, particularly for projects involving extensive concrete placements scheduled over extended periods, marking a stride towards more environmentally sustainable construction practices.

6. Conclusions

A new approach to reduce carbon emissions related to concrete constructions and mitigate global warming is proposed in this study. Considering that concrete compressive strength grows within 90 days after pouring, and that some structural elements receive deferred full loads, cement savings can be obtained when a 90-days concrete compressive strength is targeted. Machine learning and deep learning tools are hence adopted in this study to optimize the concrete mix design and reduce the cement content to target 90-days concrete compressive strength. A filtered database including 112 experimental concrete mix design records collected from a concrete plant is used to train and test the regression and artificial neural network models. Different algorithms are used and compared to find the best predictions. It is observed that for small dataset, like the one available in this study, tree-based and linear-based machine learning models outperform more complicated models, e.g., Artificial Neural Network. The Elastic Net is found to be the best algo-

Table 5
Concrete mix design based on 90-day compressive strength [1 mm = 0.039 in; 1 kN = 0.225 kip; 1 kg = 2.205 lbs.].

Nominal Compressive Strength	Concrete Slump	Nominal Maximum Size of Aggregate	Mixing Water	Cement Content	Coarse Aggregate	Fine Aggregate
30 MPa	10 cm	37.5 mm	181 kg	291 kg	1136 kg	773 kg

Table 6
LCA measure table by life cycle stages for 28-day concrete.

LCA Measures	Unit	TOTAL EFFECTS Without considering beyond building life stage	TOTAL EFFECTS considering beyond building life stage
CO_2 emissions	kg	1.99E+06	2.13E+06
Total Primary Energy	MJ	1.69E+07	1.76E+07
Non-Renewable Energy	MJ	1.65E+07	1.71E+07
Fossil Fuel Consumption	MJ	1.35E+07	1.49E+07

Table 7
LCA measure table by life cycle stages for 90-day concrete.

LCA Measures	Unit	TOTAL EFFECTS Without considering beyond building life stage	TOTAL EFFECTS considering beyond building life stage
CO_2 emissions	kg	1.81E+06	1.96E+06
Total Primary Energy	MJ	1.59E+07	1.66E+07
Non-Renewable Energy	MJ	1.55E+07	1.62E+07
Fossil Fuel Consumption	MJ	1.27E+07	1.40E+07

rithm to predict the cement content to target 90-days compressive strength with the highest accuracy (R^2 score of 0.94) and avoiding overfitting. This model is applied to a case study to assess the carbon savings related to a reduction in cement content in the optimal mix design. About 10% reduction in carbon emissions is realized in the case study, after about 10% reduction in cement content is achieved by targeting 90-days compressive strength. Whilst it is recognized that the limited size of the available dataset may affect the performance of the considered models and the selection of the best algorithm, the case study nonetheless shows promising future applications of this method.

The work presented in this paper addresses the urgent need to reduce the CO_2 emissions of concrete production without altering the production line or forcing extra expenses on the manufacturer during the deployment process. In addition, by using the current American Concrete Institute guidelines for concrete production [76], the proposed method may result in an easier implementation by the construction sector.

CRediT authorship contribution statement

Mohammadsadegh Shahrokhishahraki: Writing original draft, Data curation, Formal analysis, Methodology, Visualization, Software, Validation. **Mohammadhossein Malekpour:** Data curation, Formal analysis, Methodology, Visualization, Software. **Sajjad Mirvalad:** Conceptualization, Methodology, Supervision, Writing - review & editing, Resources. **Gloria Faraone:** Conceptualization, Methodology, Supervision, Writing - review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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