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# INTELLIGENT INITIATIVE TO REDUCE $CO_2$ EMISSIONS IN CONSTRUCTION

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**Abstract.** Global warming is one of the most important environmental issues that threatens the living on this globe so far. Carbon dioxide ($CO_2$) emission from the construction industry is one of the major sources of emissions that leads to global warming. Therefore, $CO_2$ emission reduction potentials are of additional attention nowadays. New technologies such as artificial intelligence, machine learning, and digital tools can assist this effort. Development in such technologies has made decision-making more optimized and automatic. To fulfil this aim, it is essential to have comprehensive knowledge on how emission reduction can be accomplished and what are the best decision-makings based on the new technologies of artificial intelligence and machine learning techniques. This paper provides a thorough picture of how artificial intelligence and machine learning techniques can contribute to $CO_2$ emission reduction in construction. The concepts of $CO_2$ reduction in the related derived literature are categorized into six clusters: 1) sustainable material design and production, 2) automation, digitalization and prefabrication, 3) real-world monitoring, 4) off-road vehicles and equipment, and 5) energy and life cycle assessment, and 6) decision-making and solution-based platforms. As most of the research studies in this area are related to the first cluster, i.e., sustainable material design and production, this paper has focused more on this area, and the other categories are preserved for future studies. Then, limitations and further research directions in this area are provided, which can be a valuable source for researchers in their future research.

## 1 INTRODUCTION

Greenhouse gas (GHG) emission is one of the main causes of global warming, and many countries are experiencing its adverse environmental impacts [1, 2]. Carbon dioxide ($CO_2$) is the main component of GHGs [1]. In this regard, there is an urgent need to mitigate emissions in all industries, including construction. The construction industry, accounting for emissions of up to 50%, is the largest source of GHG emissions globally [3]. Many research studies have addressed global warming concerns and the potential to mitigate $CO_2$ emissions in different stages of the construction process, i.e., preconstruction, construction, use phase and even post-disaster temporary housing and reconstruction [4-6]. The concrete industry is one of the most pollution-oriented sectors in construction. Cement production is estimated to contribute to almost 8% of global warming emissions [7].

Technology can affect $CO_2$ emissions in both positive and negative ways. Today, new and intelligent technology is required to be applied in the direction of sustainability and emission reduction [8, 9]. By transforming traditional to new construction technologies, materials, and automated practices in both hardware and soft computing aspects, there would be great potential for $CO_2$ emissions reduction in the construction industry. Internet of things (IoT), artificial intelligence (AI) and real-time monitoring, machine learning (ML), and optimization methods are among the novel practices in which the globe is shifting its direction.

Several papers have addressed using new technologies, AI and ML, for $CO_2$ emission reduction in construction [10-12]. In addition, many papers investigated designing and producing sustainable and environmentally-friendly building materials [13-18]. This particularly applies to the cement and concrete industry as being the most pollution-driven sector [19-23]. On the other hand, several papers examined $CO_2$ emission reduction on the construction sites for off-road vehicles and equipment. They tried to optimize the fuel and the activity of such vehicles [24-27]. Life cycle assessment [28-31] and real-world monitoring [32-35] are among other directions which some papers have addressed. There is a need to look at this area holistically in order to gain comprehensive knowledge to find out on what directions the previous research studies have investigated and to identify limitations, gaps and future research potentials in this area. Thus, this paper reviewed the literature's scope and provided a thorough picture of the ongoing research. The first part was dedicated to the research methods of the scoping review and papers inclusion. The second part classified the concepts existing in the derived literature and illustrated what kind of AI or ML techniques contribute to $CO_2$ emission mitigation. Finally, part three elaborated the gaps, suggestions, and future research directions.

## 2 RESEARCH METHOD

This paper is a scoping review of the research on $CO_2$ emissions reduction in construction using AI and ML. Six different directions were identified in the literature review. However, this paper has addressed the most critical direction of these six directions, as many available papers were laid in this cluster.

### 2.1 Scoping review

Scoping review is the approach used to inform the research study design in this paper. Instead of examining the depth or quality of the existing literature, a scoping review is an excellent strategy for concentrating on the range of coverage of the literature existing on a topic [36]. This was in keeping with the study's goals, which were to provide a preliminary inquiry into the scope and type of existing evidence in order to gain thorough knowledge in the field and to aid the planning of research directions studies on the subject [36, 37].

### 2.2 Data extraction, search strategy, and papers selection

The literature was searched through Web of Science and Scopus databases in the first step. The following combination of keywords (*Emissions* AND (*$CO_2$* OR *carbon*) AND *construction*

AND (*smart* OR "*artificial intelligence*" OR *AI* OR *intelligent* OR *IoT* OR "*internet of things*" OR "*machine learning*" OR *ML*)) were used in the second step to search the relevant literature. As a result, 678 papers were identified. In the next step, to decide the eligibility of the detected papers for inclusion, several criteria were considered: 1) peer-reviewed journal papers, 2) papers in English, 3) papers related to the phase of construction. This led to 345 papers. After eliminating the duplicated papers in the fourth step, 96 papers remained. In the last step, titles and abstract screenings were carried out, and 118 papers were kept. The full article review retained 80 papers for the scoping review. As this paper has only focused on the sustainable material design and production cluster, 37 out of the 80 papers were reviewed holistically (Figure 1).

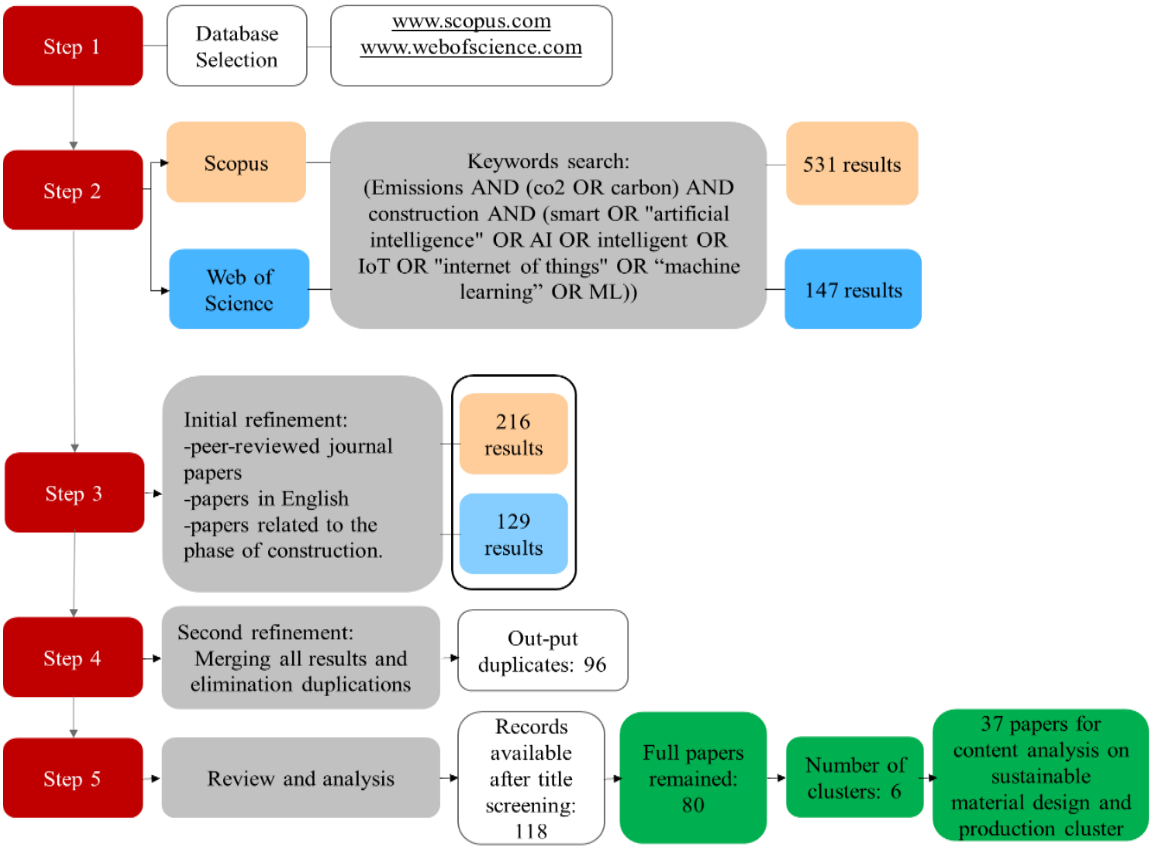


**Figure 1:** Literature screening and paper inclusion process

## 3 FINDINGS AND DISCUSSION ON $CO_2$ EMISSIONS IN CONSTRUCTION

In this part, all the concepts identified in the literature related to the initiatives to reduce $CO_2$ emissions in construction using new technologies like artificial intelligence and machine learning techniques are covered, then the gaps and future research are elaborated.

### 3.1 Content analysis of the reviewed papers

The identified papers were categorized into six clusters, including 1) sustainable material design and production, 2) automation, digitalization and prefabrication, 3) real-world monitoring, 4) off-road vehicles and equipment, and 5) energy and life cycle assessment, and

6) decision-making and solution-based platforms as shown in Figure 2. Most papers lay in sustainable material design and production cluster (having 37 records). Thus, this paper has carried out content analysis regarding this cluster.

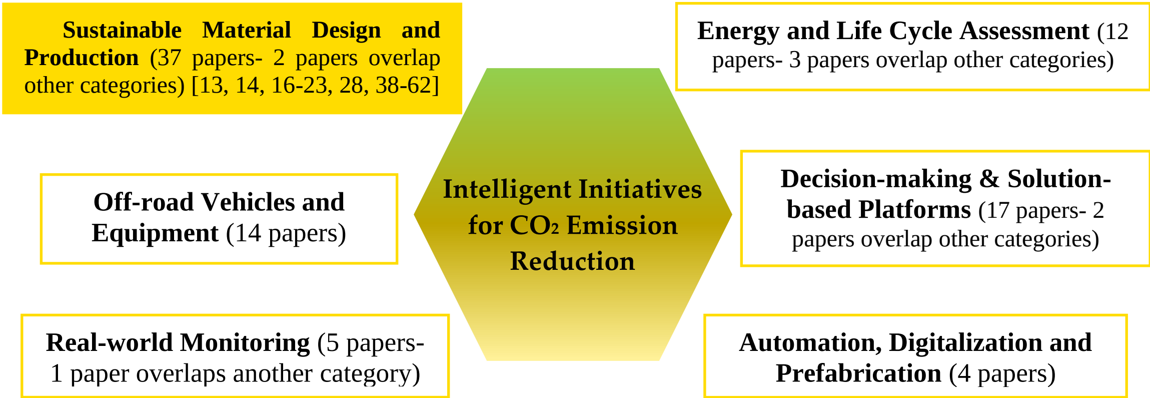


**Figure 2:** Concepts of $CO_2$ emissions reduction initiatives in construction using AI and ML

### 3.2 Sustainable Material Design and Production

Concrete and cement production are among the most pollutants industry. Many efforts have been made to reduce their impact by replacing more sustainable materials in the concrete design components and predicting their properties using ML techniques [63-66].

Long et al. [39] used calcined clay, limestone powder, silica fume, as cement substitutes for a low-carbon and low-energy 3D printable composite. Particle packing theory for the optimization of the packing density of the particle components through the particle size distribution was applied. The results show that the dynamic yield stress when composites contain 33.33 wt% calcined clay, 16.67 wt% limestone powder, and 5 wt% silica fume with sand/binder ratio of 2.5, can be significantly improved. Furthermore, the embodied energy and embodied carbon emissions per cubic meter of optimal mortar respectively decreased by 50.2% and 45.2% with respect to the plain mortar. Zhang & Zhang [19] proposed a sustainable design method for reinforced concrete members based on a discrete optimization method to reduce construction embodied emissions and costs. The study used multi-objective genetic algorithm from "cradle to site" instead of using a single-objective one at just the material production phase. The optimization was followed by the numerical examination of a case study to compare the Pareto optimal solutions for singly- and doubly-reinforced concrete beams. The results showed that an extra cost of 5–6% can make up for a 14.7% of emission reduction. Trinh et al. [13] introduced a method for carbon-based optimization (minimum $CO_2$ emissions) of a flat plate reinforced concrete building using Branch-and-Reduce deterministic algorithm. Different case studies with different slab spans and floor levels were optimized. The Branch-and-Reduce Optimization Navigator commercial package and genetic algorithm solver of MATLAB were applied for the optimization. The results showed that the optimized one reduces 5–17% embodied carbon compared to conventional buildings. The proposed method decreases 31% of the total embodied carbon compared to the genetic algorithm method. Wimala et al. [48] introduced an artificial neural network (ANN)-based model to predict $CO_2$ emissions of producing precast concrete. First, a survey was carried out for 107 plants precast concrete in Japan to acquire data on the $CO_2$ emission factors. Six factors of ordinary Portland cement

(OPC), fine aggregate, coarse aggregate, electricity, kerosene, and heavy oil were considered using Principal Component Analysis to serve as the inputs of ANN model for $CO_2$ emissions forecasting. A backpropagation neural network technique with three-layer perceptron was introduced to train the network. The network model having 51 hidden neurons with a set of 0.1, 0.3, and 0.9 for learning rate, initial weight, and momentum, respectively, generated the best result. Mean absolute percentage error value below 10% revealed that ANN could predict $CO_2$ emissions in producing precast concrete with significant accuracy.

Huseien et al. [41] examined substituting cement with fly ash (FA) and effective microorganism (EM) at an optimized proportion to produce sustainable concrete with lower $CO_2$ emission and boosted mechanical properties. The amount of EM and FA as cement substitution was determined in four different ratios of 10, 20, 30 and 40% and various water ratios. Adaptive neuro-nuzzy inference system was employed to test the compressive strength of the laboratory-based database. The results revealed that the optimal mixture obtained for the specimen with OPC replacement with 10% FA and EM operated optimally resulted in compressive strength of 50 MPa, 41.5% lower carbon dioxide, 39.4% less energy consumption, and 24.8% lower cost. Kordnaeij et al. in [52] & [18] replaced partial cement with a more environmentally friendly zeolite material. In [18], they conducted a lab-based study to examine the impact of several factors, including sand size, water/binder ratio, and cement replacement percentage with zeolite, on the compressive strength of the specimens. Multiple regression model (MLR) and a group method of data handling (GMDH)-type neural network were applied to predict the compressive strength of zeolite-cement grouted sands. In [52], the authors applied MLR and a kind of ANN (GMDH) to predict the small strain shear modulus in zeolite–cement grouted sands. The small strain shear modulus function included three water to binder ratios (w/b) parameters, average sand grain size, and cement replacement with zeolite percentage. Active compounds were applied as input factors to consider the concurrent impact of zeolite percentage and w/b ratios on the shear modulus of grouted sands. The results revealed that MLR and GMDH techniques for predicting small strain shear modulus of grouted sands perform better when considering active compounds as an input factor than considering w/b and zeolite percentage as input factors. Applying active compounds to predict small strain shear modulus of grouted sands by the GMDH models led to about 35–41% prediction improvement. The GMDH-based model performed more efficiently than the MLR-based one.

Ma et al. [56] applied a highly effective stabilizer based on cement and embedded FA to create a more environmentally friendly earth-based construction. Several parameters such as FA content, stabilizer content, physical indexes, and curing duration were considered to conduct a hybrid strength and embodied $CO_2$ index measurement. MLR and power regression methods were employed in this study. The results revealed that the $CO_2$-equal emission of the cement-based high-efficiency stabilizer was lower than that with cement in the context of the same strength. The introduction of FA into stabilizer decreased the CO2-equal emission to some extent. This indicates that cement-based high-efficiency stabilizer is cleaner than cement, even though several chemical additives have higher $CO_2$-equal emissions. Abbey et al. [58] replaced partial cement with ground granulated blast slag (GGBS) and pulverized fuel ash (PFA) for deep soil concrete to improve the compressive strength and reduce $CO_2$ emission. Different mixes of cement, cement with PFA, and cement with PFA and GGBS were tested at 7, 14, 28, and 56 days. MLR was used for the prediction of the unconfined compressive strength. Soil with less plasticity compared to that with higher plasticity indicated greater compressive strength. Adding GGBS and PFA reduced the cement content, leading to cost and $CO_2$ emissions reduction. The proposed method provided reliable and accurate prediction for compressive strength for weak soil with unified compressive strength less than 25 kPa, and for the proportion of w/b. Cement compositions with PFA and GGBS for deep soil mixing were appropriate for soil consolidations and highway embankments. The model was validated using different compositions of binders. Park et al. [23] investigated the potential application of crumb rubber made from recycled tires in geopolymer concrete to diminish cement content, which leads to $CO_2$ emissions reduction. The effects of aggregates size and amount, the molarity of sodium hydroxide, curing method and time parameters on compressive strength were examined. Sodium silicate, sodium hydroxide liquid mix, FA, and crumb rubber were utilized in the geopolymer concrete. The regression model was applied to recognize important parameters and their interactions and decide on the strength of geopolymer concrete. It showed that the relationship between rubber substitution and other factors was not significant. The ANOVA technique showed that the best proportion for crumb rubber is up to 5 % with 95% confidence level in three kinds of FA. Suitable proportion of rubber substitution could be applied without significant strength reduction. Fairbairn et al. [61] replaced cement with sugar as a by-product at the industrial level with the aim of reducing $CO_2$ emissions. Sugar cane bagasse ash is a pozzolan that can be used as a substitution for cement to boost the cement-based mixture properties. A simulation based on United Nations Framework Convention on Climate Change for the Clean Development Mechanism was carried out to assess the possibility of a reduction in $CO_2$ emissions. Because the average distance between cement plants and sugar cane/ethanol factories is one of the major variables in estimating $CO_2$ emissions, a genetic algorithm was created to handle this optimization challenge. Over 60% of the country's sugar cane and ash production and a significant number of cement plants—located in Sao Paulo (Brazil)—were selected as a case study. In total, around 520 kilotons of $CO_2$ were estimated annually to be reduced by applying this United Nations Framework approach. Table 1 summarizes the ML techniques applied to design and produce sustainable materials.

**Table 1:** Sustainable Material Design and Production using ML techniques

| **Sustainable Materials** | **Soft Computing Method/ Digital Tool** | **Output** | **Reference** |
|---|---|---|---|
| Bioinspired sandwich carbon-fiber reinforced polymer | Taguchi method Response surface methodology–multiple objective optimization | -Substitution for steel in the recycled concrete beam that leads to $CO_2$ emissions reduction<br>-Lightweight and 0.73 to 4.4 times better than steel reinforced concrete structures in terms of fracture toughness, cost-effectiveness<br>-Suitable for semi-automated systems & 3D printing | [38] |
| Silica fume concrete | Hybrid beetle antennae search algorithm– back propagation neural network | Trade-off between embodied emissions and financial costs. An extra cost of 5–6% can make up for a 14.7% of emission reduction. | [20] |
| Ocean-borne plastic flakes cement mortar | Regression | Ocean-borne plastic flakes as fine aggregate (specific gravity: 2.47, water absorption: 3.5). Not to be used in structural members. | [40] |
| Industrial byproduct-based | Optimized hybrid model of principal component analysis – | -Mixtures with high content of FA had the least EE and $CO_2$ emissions. | [43] |

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|---|---|---|---|
| alkali-activated mortars | optimized artificial neural network – combined with the cuckoo optimization algorithm | -Mixtures with high content of POFA and GBFS had the most rate of EE and $CO_2$ emissions.<br>-All the above have less EE and $CO_2$ emissions in comparison to the OPC-based mortar. | |
| Sustainable self-compacting geopolymer concrete | Optimized artificial neural network combined with metaheuristic Bat optimization method | Applying 50% of FA in the GBFS-FA composition in self-compacting geopolymer concrete obtained suitable strength as well as environmental impact mitigation. | [42] |
| Green bentonite and palm bunch ash concrete | Fuzzy logic technique | Applying 5% of palm bunch ash and bentonite as a replacement for cement led to the maximum compressive strength, thus, to green concrete with less environmental impact. | [44] |
| Hemp-based bio-composite | AI-based gene expression programming technique | -The compressive strength and thermal conductivity were mainly influenced by plant aggregate to binder, water to binder ratio, and density of bio-composite.<br>-Bio-composites absorbed 14 to 35 $kg/m^3$ $CO_2$ from the environment. | [16] |
| Oil palm shell Concrete | Hybrid AI model based on random forest–modified beetle antennae search algorithm | -The model has high prediction accuracy with a correlation coefficient of 0.96 on the test set.<br>-Along with appropriate compressive strength, the oil palm shell concrete led to $CO_2$ reduction, natural resources conservation, and cost-efficiency. | [67] |
| Recycled aggregate concrete | K-nearest neighbor, regressors, random forest (RF), support vector machine (SVM), backpropagation neural network (BPNN), multi-objective optimization model based on AI algorithms and multi-objective firefly algorithm | -RF and BPNN gained the best accuracy performance for predicting compressive and splitting tensile strength of recycled aggregate concrete, indicated by the highest correlation coefficients (0.9064 and 0.8387, respectively) and lowest root-mean-square errors (6.639 and 0.5119 MPa, respectively).<br>-The model successfully optimized the recycled aggregate concrete mixture proportions for the $CO_2$, cost and compressive strength trade-offs. | [45] |
| High and ultra-high strength concrete | Artificial neural network (ANN), Gaussian process regression (GPR), support vector machine (SVM), decision trees (DT), linear regression (LR) | Several supervised machine learning techniques of ANN, GPR, SVM, DT, LR were applied to produce new concrete design compositions with low embodied carbon and defined compressive strength. More than 700,000 designed compositions were analyzed. The results revealed that the ANN showed the best function while the LR was the worst. | [28] |
| Sustainable OPC concrete | Meta-heuristic-based technique: Six machine learning techniques, including water cycle algorithm, soccer league competition algorithm, genetic algorithm, artificial neural network, support | -Water cycle algorithm was selected as the most accurate algorithm, among others.<br>-Six mixtures gained appropriate performance in the trade-off of all defined criteria of compressive strength, cost, environmental impacts (including embodied $CO_2$ emission, and energy and resource consumptions). The most sustainable mixture gained a sustainability index of 1.9625. | [17] |

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|---|---|---|---|
| | vector machine, and regression | | |
| Waste sawdust-based lightweight alkali-activated concrete | Artificial neural network | -The compressive strength of the concrete with 100% of sawdust as a replacement for natural aggregates was 48.6. This formulation decreased $CO_2$ below 85% fuel production compared to one with natural aggregates.<br>-Cubic-shaped molds of size 100×100×100mm cured for 1, 3, 7, 28, 56, and 90 days following the ASTM C579 specification were applied. | [47] |
| Low $CO_2$ slag-blended Concrete | Genetic algorithm | -Concrete with various strength levels (w/b ratios from 0.20 to much higher), different slag substitute levels (slag replacement ratios from 0 to 80%), and various curing conditions (curing temperatures of 5 $^{o}$C to 80 $^{o}$C)<br>-Strength development model: the slag substitute ratios were 25%, 50%, and 75%, and the compressive strength was measured at 1 day, 3 days, 28 days, and 18 months. | [50] |
| Low–cost and low–$CO_2$ blended concrete | Gene expression programming, genetic algorithm | Regression was performed on concrete compressive strength at 28 days as a function of the w/b ratio, the fly ash to binder ratio, the slag–to–binder ratio, and the water content | [49] |
| Supplementary cementitious materials | Response surface methodology | - Three samples for every single mix at 7 and 28 days as per IS 516-1959 specification, cubic specimens of 150×150×150 mm, cylindrical specimen (d×h) of 150×130 mm and prism specimens of 100×100×500 mm were cast to find the variation of compressive strength, splitting tensile strength, and flexural strength, respectively.<br>- 20% alccofine substitution for cement, gained better durability and mechanical features in comparison to other mixes | [22] |
| Lightweight Concrete | Artificial neural network | -Six cubic samples for each lightweight concrete 1-15<br>-Compressive strength test on the 28$^{th}$ day<br>-The highest compressive strength was determined with glass ash aggregate ratio of 75% and 100% with 21.35 MPa and 18.65 MPa, respectively.<br>-Use of 25% of granulated expanded glass aggregate resulted in about a 13% increase in concrete compressive strength, a 12% decrease in density, and a 15% decrease in porosity. | [51] |
| Recycled aggregate concrete | Optimization method of Los Angles test machine through Ball Milling Method | -0–20–40–60% recycled aggregate and improved recycled aggregate mixes. Two cylindrical specimens with an aspect ratio (h/d) of 2 and prismatic specimens with an aspect ratio of 5 were stored in lime-saturated water at until 28-day. | [53] |
| Concrete mixture | Adaptive surrogate model<br>genetic algorithm | -15 samples points of three different types of concrete (C70, C40 and C30) from the Kaili concrete plant with 28 days of curing.<br>-when the content of FA and phosphorus slag are 99.27 kg/m3, 152.99 kg/m3 and 113.56 kg/m3 and 191.61 kg/m3, 101.39 kg/m3 and 103.01 kg/m3, respectively, cost and CO2 emissions of C70, C40 and C30 concrete are the lowest. | [54] |

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|---|---|---|---|
| Environmentally friendly cementiti ous material | Multi-regression model | -GGBS substituted OPC at different percentages: 10, 15, 20, 25, 30, 35, 40, 45 and 50% by mass of OPC to reduce $CO_2$ emissions.<br>-Three samples of dimensions 40×40×160 mm, two halves by three-point loading of the prism specimens and averages of six halves were taken to represent the final values for compressive strength.<br>-At 3, 7, 28 and 56 days of curing and compared with that of the reference cement samples. | [55] |
| Cementless mortar using hwangtoh binder | Nonlinear multiple regression | -Cement replacement by hwangtoh<br>-Cubes of 50mm, compressive strength at 1, 3, 7, 14, 28, and 91 days in temperature 23+/-2 C and relative humidity of 70+/-50%<br>-Compressive strength increases gradually while increasing the volume fraction of fine aggregate but decreases at fine aggregate/hwangtoh binder ratio of 3.5 | [62] |

## 5 GAPS AND SUGGESTIONS FOR FUTURE RESEARCH

There are several directions future research studies can address. For sustainable concrete development, investigating the quality depreciation and materials loss in the recycling process by considering a broader range of input variables (e.g., cement type, curing conditions, aggregate types and grading) is recommended to increase the generalization ability of the proposed model. Furthermore, more intelligent models need to be developed to design/predict different concrete mixtures (with different types and volumes of supplementary materials such as fly ash, slag, silica fume, manufactured sand, mineral coarse aggregate, and fibres, etc.) that minimize construction and environmental costs, reduce $CO_2$ emissions, and maximize favorable mechanical properties.

More accurate data is needed for training and testing the multi-objective optimization model. This ensures more refined tuning of hyperparameters and further improves the ability of the model to obtain meaningful patterns from data with noise. Improving the mathematical model by modifying the model scenario and employing other solution methods for multi-objective optimization, applying more improved and new prediction models capable of predicting the compressive strength of OPC, introducing advanced data pre-processing techniques such as missing data imputation and semi-supervised learning to replace the input and output missing values in the database are suggested for future research. Upgrading optimization algorithms and extending the proposed algorithms to solve reliability optimization of trade-off time, cost, quality, labor, and carbon dioxide emission factors in generalized construction projects are other future directions.

## 6 CONCLUSIONS

The paper provides a scoping review of the initiatives for $CO_2$ reduction using AI and ML in the construction sector. The related papers were identified, and the concepts of carbon dioxide reduction using AI and ML methods were categorized into six clusters of 1) sustainable material design and production, 2) automation, digitalization and prefabrication, 3) real-world monitoring, 4) off-road vehicles and equipment, and 5) energy and life cycle assessment, and 6) decision-making and solution-based platforms. As almost half of the papers belonged to the sustainable material design and production cluster, this paper has focused on giving a holistic picture of this area and to find the gaps and future research. Reviewing other clusters are preserved for the authors' future study. Various AI and ML techniques such as artifiacial neural network, genetic algorithms, regression models, support vector machines, and decision trees were used to predict and design sustainable building materials and compositions. These tools help in more automatic and accurate prediction and optimization of sustainable building materials' design and production to reduce $CO_2$ emissions.

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