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Research article

Use of operational research techniques for concrete mix design: A systematic review

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ABSTRACT

Traditional methods for designing concrete mixtures provide good results; however, they do not guarantee the optimum composition. Consequently, applying operational research techniques is motivated by an increasing need for designers to proportion the concrete's raw materials that satisfy the concrete performance requirements such as mechanical properties, chemical properties, workability, sustainability, and cost. For this reason, many authors have been looking for mathematical programming and machine learning solutions to predict concrete mix properties and optimise concrete mixtures. Therefore, a comprehensive review of operational research techniques concerning the design and proportioning of concrete mixtures and a classification framework are presented herein.

1. Introduction

Concrete is one of the most commonly used construction materials in the world. Due to its unique feature combination of workability, mechanical properties, durability, and the wide availability of raw materials sources, concrete has become highly attractive for many applications in the civil industry [1]. Generally speaking, concrete can be defined as the mixture of a cement paste and water with fine and coarse aggregates. However, a concrete mix can be way more complex and have a wide range of constituents. It can be combined with materials, such as cement, pozzolans, fly ash, blast-furnace slag, silica, recycled concrete aggregate, polymers, fibres, and superplasticisers. Due to the vast possibility of constituents and the different variations in composition, it is possible to obtain a concrete mixture with different physical and chemical properties. Therefore, varying the components and their quantities allows the properties of both fresh and hardened states to be tailored to achieve the design specifications.

Each concrete application in the construction sector will require a specific mix composition to satisfy the performance requirements, such as workability, durability, and compressive strength. Therefore, designing good concrete is utterly vital to guarantee that the mixture will achieve the required specifications. In order to meet the best composition of concrete, designers have adopted concrete mix design to find an optimal concrete mixture. This procedure is defined as selecting suitable raw materials and proportioning the quantities of each constituent in order to produce a final product that meets the desired physical and chemical properties [2]. For this reason, promising development in the concrete mix design step can guarantee improvements in physical-mechanical performance, more outstanding durability of structures, and a reduction in production costs.

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Most of the available mix design methods are based on empirical relationships, charts, and graphs developed from experimental investigations. They follow the same principles, and only minor variations exist in the mix design methods in selecting the mix proportions [3]. Some traditional methods for proportioning concrete are the American Concrete Institute (ACI) mix design method and the British mix design method [4]. According to DeRousseau [1], the conventional mix proportion classification can be broken down into two main methods: prescriptive specification and performance-based specification. The main difference between the two methods is that the first follows a step-by-step procedure to determine the quantity of each component. On the other hand, the second method does not require strict guidance. According to the design specification, a value of a required property is established; then, the designer can select any amount of cement, water, and aggregates and verify that the mixture achieves the value of the required property.

Although these traditional methods are way useful, the mathematical relationship between variables and the mixture composition can have some drawbacks. The first drawback of current concrete design methods is the lack of contemplation of Supplementary Cementitious Materials' influence (SCMs) on concrete properties. Since SCMs have been used lately to replace a portion of cement, they are prone to dramatically impact mechanical properties such as compressive strength [4]. Another drawback is that the mix design does not capture the true complexity of the relationship between the mixture design and the concrete's properties. The type and quantities of each material used are variable, and the estimation of these properties cannot be quantitatively and precisely evaluated. Lastly, the current concrete design methods do not present optimised values of concrete properties. The methods meet a satisfactory composition of the concrete constituents that reach the desired values of the properties. However, choosing a specific design does not guarantee that it is not an optimal concrete mix solution.

Besides the traditional methods, some research lines encompass the design of experiments to identify a good concrete mix composition. Compared to traditional methods, the application of the design of experiments can exhibit better solutions due to the numerous experiments. Although several studies have been investigating the problems related to concrete mix design, the optimisations of experimental design can undergo exponential growth if they increase the number of variables and their values [1]. Furthermore, due to the high degree of non-linearity between the dependent and independent variables, the regression models obtained to predict the properties of the concrete can hardly present a precise regression equation [5].

Therefore, both procedures have disadvantages and do not meet an optimised mix composition. For this reason, the computational aid system has been studied over the years in order to solve the problems regarding concrete mix design [6]. It formulates the problem by more accurately modelling the relationships between variables and the output response, leading to an optimal solution [7]. Thus, mathematical programming and machine learning have been prominent in the literature among the operational research techniques used to solve mixture proportioning issues. Both methods can be employed separately or as complementary approaches, frequently used to solve various engineering problems. Considering this fact, many researchers look to predict the properties of concrete in a more accessible, less costly, and less time-consuming way [8]. On the other hand, others seek to develop a more economical and sustainable concrete mix [9].

Several papers in the literature reviewed mathematical models and machine learning techniques in predicting concrete properties or the optimal composition of concrete. Chaabene et al. [10] examined machine learning (ML) models to forecast the mechanical properties of concrete. Another work presented a systematic review of the ML algorithms employed to predict compressive strength [11]. Besides that, Song et al. [12] reviewed the current literature on optimising mixing ratios using ML and metaheuristic algorithms, which offers insight into the continuous development of models in the field of hybrid optimisation. Based on these previous works, this article aims to examine relevant articles that have solved the concrete mix design problem using two types of operational research techniques: machine learning and mathematical programming. The novelty of this article lies in the lack of review articles focusing on these two techniques applied to the concrete mix design, which can bring a holistic understanding of the employment of these tools. Additionally, this article intends to propose a classification framework with the main features of the last works using mathematical programming or machine learning to solve problems with concrete mix design.

To place things into context, three major questions are addressed in the paper:

1. What are the main machine learning algorithms that have been used in order to come up with the concrete mix design?
2. What are the mathematical optimisation algorithms that have been used in order to help concrete mix design?
3. How is the literature linking both aspects, mathematical optimisation and machine learning, in order to design a concrete mix?

The rest of the paper is organised as follows: Section 2 briefly describes the concrete mix design research background. Next, section 3 describes the adopted study review methodology, presenting a systematic review and proposing a classification framework. The following section, section 4 evaluates the concrete mix design studies. Next, section 5 brings a discussion of the general findings. Finally, the final section contains concluding remarks on the general findings and research proposals.

2. Background

Before describing the proposed classification framework, some essential aspects of concrete mix design are summarised. Then, Section 2.1 and Section 2.2 outline mathematical optimisation models and machine learning methods adopted as solution strategies for the concrete mix design.

2.1. Overview of mathematical programming techniques

Mathematical models and computational optimisation methods are alternative solutions in concrete mix design to tackle the traditional methods and the time-consuming laboratory experiment optimisations. While the optimisation methods bring an optimal or near-optimal solution with low computational effort, the others only lead the designers to an ideal solution, which cannot be the most improved. These approaches initially establish one or more objectives (e.g., concrete properties) as functions of the decision variables (e.g., concrete constituents). Then, they search for the optimal concrete mixture by adopting optimisation algorithms. Mathematical methods can be classified into meta-heuristic, heuristic, and exact methods. Most researchers have frequently implemented them in the concrete mix design field to deal with mix design issues.

2.1.1. Exact methods

Exact methods have been used for a long time in mathematical optimisations and are very effective in modelling and optimising the properties of concrete. We can elucidate some model examples among the exact methods, such as linear [13], non-linear [14], and mixed programming [15]. Many authors have applied exact methods to estimate the optimal composition or predict other concrete properties. For instance, Jin et al. [15] proposed non-linear and mixed regression models to predict concrete strength based on mixture-design variables and curing age. The proposed model achieved higher accuracy than the linear method using the same variables and datasets. Another study that used non-linear programming was Habibi and Ghomashi's work [16]. Two mathematical models were developed based on sequential quadratic programming to optimise the self-compacting concrete mix design, minimising cost with compressive strength and slump as constraints. Miller et al. [17] developed a linear method for predicting Global Warming Potential (GWP) from concrete production and compressive strength for concretes containing replacement binder. The work proved the equations were suitable for predicting compressive strength and GWP for mixtures containing replacement binder. Fan and Miller [18] also took environmental problems into account. They developed a set of mathematical equations to find minimum Greenhouse Gas (GHG) emissions and to dictate the required concrete mix proportions, based on water-to-binder ratio and supplementary material, to achieve optimised GHG emissions. Li et al. [19] proposed a numerical simulation algorithm for calculating the overall elastic properties of ordinary concrete, which involves the finite element method in combination with Monte Carlo simulations. Comparisons with experimental test results of elastic modulus and Poisson's ratio indicated a good agreement with the proposed model.

2.1.2. Heuristic and metaheuristic methods

Heuristic and metaheuristic methods are higher-level procedures aiming to find, develop, or select an algorithm that may provide a sufficiently good solution to an optimisation problem, especially with incomplete information [20]. While many heuristic algorithms are very specific and problem-dependent, a metaheuristic is a high-level problem-independent algorithm. Regarding concrete mix design issues, many studies have been using different heuristic metaheuristic methods to predict and optimise the properties of concrete. For example, Lee et al. [21] applied Harmony Search (HS) algorithm to find the optimum mix proportion satisfying the required strength and slump. The results showed that the HS algorithm could be a potent tool for high-performance concrete mix proportioning compared with other methods. Moayedi et al. [22] investigated the efficiency of the Ant Lion Optimisation (ALO) algorithm to predict the concrete slump. Besides, they compared it with Biogeography-Based Optimisation (BBO) and Grasshopper Optimisation Algorithm (GOA). The findings revealed that ALO outperformed both models. Another study [23] applied an Artificial Bee Colony (ABC) algorithm to predict chloride penetration in self-consolidating concretes. Comparisons among ABC and Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) were conducted and showed higher reliability [23].

Among the metaheuristic methods used to solve concrete mix design problems, many studies applying a genetic algorithm or some variation of swarm optimisation are notorious. For example, to improve the anti-cracking performance of high-strength concrete, Yue et al. [24] used GA to optimise concrete mix proportioning by minimising the cracking risk coefficient. Comparisons between a control concrete and the optimised one showed that crack resistance was considerably improved, and a reduction of 25% of the crack risk coefficient was achieved. Furthermore, Awoyera et al. [25] modelled the compressive strength, split tensile strength, and flexural strength of geopolymer concrete using gene expression programming, which showed a good prediction.

Regarding the swarm optimisations, Mashhadban et al. [7] investigated fibers' effects on self-compacting concrete properties using a hybrid model composed of PSO and a neural network. The model predicted splitting tensile strength, flexural strength, compressive strength, and fracture energy with a high level of accuracy. On the other hand, Kandiri et al. [26] estimated the compressive strength of the ground granulated blast furnace slag concrete by applying a multi-purpose Salp Swarm Algorithm (SSA).

Besides that, some authors have been employing other optimisation tools. For example, Knor et al. [27] applied a numerical solution based on the inverse heat transfer problem (IHTP) and direct search optimisation to investigate the thermal properties of hardening concrete, i.e., specific heat and thermal conductivity. Pazouki et al. [28] proposed a hybrid method using a neural network and firefly optimisation algorithm to predict and optimise the compressive strength of self-compacting concrete containing fly ash.

2.2. Overview of machine learning techniques

Machine learning is considered a branch of artificial intelligence that uses several algorithms to learn from the data. The learning step allows its behaviour to be modified based on its own experience, i.e., the system can predict or classify data based on previous data [29]. This behavioural modification consists of establishing some logical rules according to the input data to explore the potential of hidden patterns in the data used and improve the performance of a specific task. The use of these techniques allows the designers or the decision-makers to predict some desired outputs and choose a cleverer and more assertive decision regarding the properties of concrete [30].

The techniques have an outstanding performance in data processing and a remarkable ability to model the properties of concrete without explicit knowledge of the relationships between the properties of concrete and the variables [31]. For those reasons, they have been extensively used to model various properties of different types of concrete and solve concrete mix design issues. Another factor encouraging machine learning is the development of new types of concrete and the lack of mixing design guidelines, which can be noted in the Portland concrete guidelines that do not consider the new types of concrete developed.

With technological advancement and the search for more sustainable building materials, researchers have been looking for alternatives to replace part of the cement and aggregates, aiming to reduce CO_2 emissions and improve the quality of concrete. However, although the works regarding these materials are increasing, guidelines and standards do not cover concrete mixtures with these substitutions for common concrete mixtures. In addition, some types of concrete, such as fly ash-based geopolymer concrete, rubberised concrete, and recycled aggregate concrete, do not have specific guidelines to guarantee a good concrete mixture.

Machine learning has recently gained prominence in several areas, including the construction sector. Besides that, due to its accuracy in property predictions, some researchers have been efficiently applying these algorithms to solve concrete mix issues. The most used machine learning techniques in the literature to solve the concrete mix design issues can be broken down into five broad categories: Artificial Neural Networks (ANN); Support Vector Machine (SVM); Decision Trees (DT); Linear Regression; and Logistic Regression (Fig. 1). The first three categories are the most employed in concrete mix design predictions and optimisations.

2.2.1. *Artificial neural networks*

Artificial neural networks (ANN) are one of the most widespread machine learning techniques [32]. This model is inspired by the human neural system and the learning ability of the human brain. Its schematic representation consists of several layers of interconnected neurons responsible for letting the information flow from one neuron to another. Although the number of layers and neurons is directly related to the type of problem to be studied, ANN is generally composed of an input layer with the influencing variables, an output layer with the desired predicted variables, and at least one layer hidden between them. Yeh, a pioneer in this field, published some distinct works that influenced the development of the new architecture of ANN [33]. For instance, one of his works showed a higher accuracy of the strength model based on ANN when compared to a regression analysis model [34]. Furthermore, among his recent works, some models are analysing the strength of concrete using the design of experiments [35] and the accuracy of a neural network to predict the slump flow [36].

Different types of ANN are applied to solve concrete mix design problems in the literature. The ANN most used in modelling the prediction of concrete mixture properties are Feed-forward Neural Network (FNN) and the Backpropagation Neural Network (BPNN) approaches. To elucidate some examples, Yaprak et al. [37] applied a Feed-forward Backpropagation Neural Network (FBPNN) algorithm to predict the concrete compressive strength using different cement types, ages, and cure conditions as input parameters. Shahmansouri et al. [38] also predicted the compressive strength of geopolymer concrete using FNN, varying the specimen's age, NaOH concentration, and contents of neozolite, silica fume, and ground granulated blast-furnace slag. Yue et al. [24] applied FNN to

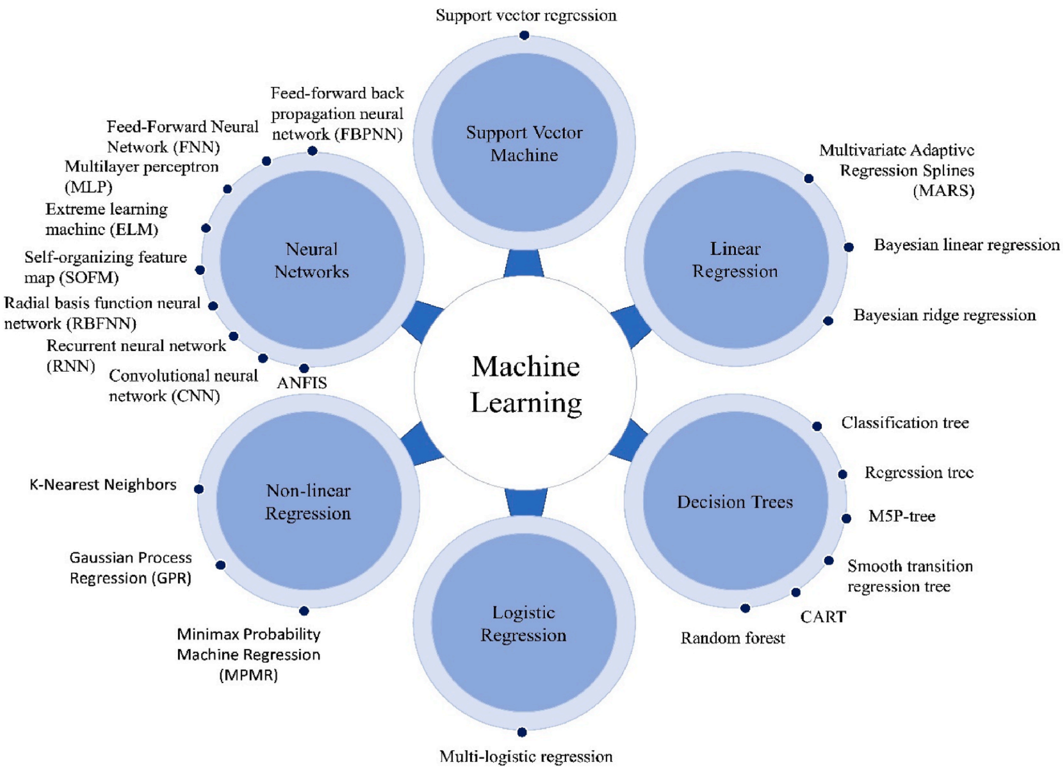

Fig. 1. Main machine learning techniques used to solve concrete mix design problems.

predict concrete slump, compressive strength, tensile strength, and elastic modulus. Regarding BPNN, while Verm et al. [39] predicted the compressive strength by implementing this algorithm for fly-ash blended cement concrete mixes, Kellouche et al. [40] used BPNN to analyse the carbonation depth of fly-ash concrete. Both works indicated good agreement with the experiment results.

Other types of ANN have also been used frequently to predict concrete properties. One model widely applied to problems with concrete mix design is Multilayer Perceptron (MLP). Abbellán-García [41] applied MLP to predict the 28-day compressive strength of ultra-high-performance concrete using different combinations of supplementary cementitious materials:silica fume, fly ash, slag, glass powder, rice husk ash, fluid catalytic cracking residue, metakaolin, and limestone powder. Sargam et al. [30] compared nine machine learning algorithms, and the MLP model indicated a higher accuracy.

Besides these models, a few works employed other techniques. For example, Zhang et al. [42] established a strength prediction model of rubber fibre concrete using the Extreme Learning Machine (ELM), which showed that the model has high accuracy compared with other models as a conventional neural network. Nunez et al. [29] deployed a novel Recurrent Neural Network (RNN) to predict the compressive strength of recycled aggregate concrete. The model effectively captured the underlying features contributing to the compressive strength of the concrete. Czarnecki et al. [43] compared two ANN, Self-Organizing Feature Map (SOFM) and MLP, for predicting the compressive strength of cementitious composite containing ground granulated blast slag. Al-Mughanam et al. [44] implemented an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to predict the compressive strength of self-compacting concrete containing treated palm oil fuel ash as a partial cement substitution. All of these models indicated high-efficient performance inpredicting the properties of concrete.

2.2.2. *Support vector machine*

The Support Vector Machine (SVM) is another machine learning technique highly chosen in concrete properties prediction. SVM is associated with learning algorithms that analyse regression and classification analysis data. According to Suykens and Vandewalle [45], SVM is a powerful and versatile method to deal with linear/non-linear classification, regression, and even outlier detection. The main important objective of the SVM classifier is to separate different classes with the most significant possible margin between two of them. In contrast, Support vector regression (SVR), a subset of SVM, tries to fit as many instances as possible on the street while limiting margin violations [46].

To name a few works applying SVM or SVR, Salimbahrami and Shakeri [47] adopted the SVM method to estimate recycled concrete's compressive strength. ANN and SVM techniques were compared, and although the results indicated SVM as an effective tool, its predictions are far closer to ANN. Besides, Thilakarathna et al. [48] carried out embodied carbon analysis using a set of machine learning algorithms to minimise the carbon footprint of high-strength and ultra-high-strength concrete without jeopardising the mechanical properties of the concrete. The outcomes found in this work were in good agreement with the ones discovered by Salimbahrami and Shakeri. On the other hand, Liu et al. [49] used SVM to predict the autogenous shrinkage of conventional concrete mixtures, and SVM was as accurate as ANN prediction. Other work introduced an advanced version of SVM, least-square SVM, to predict pervious concrete's permeability coefficient and compressive strength [50].

2.2.3. *Decision trees*

The Decision Trees (DT) methods also belong to the supervised learning family and can be applied to solve classification and regression problems. This predictive modelling is represented in a tree structure, where the leaves represent class labels and branches represent the characteristics set that lead to those class labels [48]. Due to its simplicity, some authors use this technique to estimate the properties of concrete mixtures. Random Forest (RF) and M5P trees stand out among the DT algorithms in this research area. Asthe other two methods of ANN and SVM presented previously, DT is also used to predict various properties of concrete.

For example, Gomaa et al. [51] modelled an RF model to predict slump flow and compressive strength as functions of influential parameters of the alkali-activated concrete. The model showed high efficiency in predicting both properties. Han et al. [52] presented an ensemble of ML models formulated by combining RF and SVM to predict the modulus of elasticity of recycled aggregate concrete, which produced more accurate results than those yielded by either standalone ML models. Behnood and Golafshani [53] studied the efficiency of the M5P algorithm in developing predictive models for the mechanical properties of concretes containing waste foundry sand as a partial or total replacement for fine aggregate. This research indicated a successful use of the M5P tree in generating predictive models for compressive strength, modulus of elasticity, flexural strength, and splitting tensile strength.

In addition to the tree-based techniques mentioned above, researchers like Anyaoha et al. [14] and Feng et al. [54] also used other DT techniques to predict the concrete's properties. The former used a boosting ensemble of Smooth Transition Regression Trees (STR-Tree) and a boosting algorithm to create a more robust model. The developed model predicted the compressive strength of high-performance concrete using its constituents and mixture proportions as input variables, which showed its dominance in prediction accuracy over the other methods. The latter employed an adaptive boosting algorithm integrated into weak models, such as Classification and Regression Tree (CART), ANN, and SVM. The outcomes indicated CART as the higher performance for the compressive strength prediction of concrete containing slag and fly ash.

3. Review methodology

The systematic method adopted in this review aimed to address the research questions elucidated in the introduction section. Therefore, the review methodology can be broken down as follows:

Step 1. The first step is related to the search process for articles involving the concrete mix design topic and selecting the most relevant articles, which fit more into the scope of the questions raised.

Step 2. The second step involves analysing the previously selected articles to specify the general characteristics of the mathematical optimisation modelling and machine learning techniques used in this subject.

Step 3. The third step encompasses the development of a classification framework linking the predicted properties and the methods applied for the prediction and optimisation of concrete mixtures.

Step 4. Finally, the last step involves the evaluation of the material based on the proposed framework.

3.1. Systematic review search

The review search was conducted to find and select the most relevant articles. In order to ensure this, a set of keywords was well-defined. Two main groups of keywords have been used to find the literature related to concrete mix design problems:

Group 1: Words related to concrete mix design: “Concrete Mix Design”; “Concrete Mixture”; “Concrete Proportioning".

Group 2: Words related to mathematical modelling or machine learning: “Mathematical Programming”; “Mathematical Modelling”; “Optimisation”; “Algorithm”; “Metaheuristic”; “Machine Learning".

Combining the two groups, a general search query was achieved with the mais essential keywords and then employed on academic databases, including Scopus and Science Direct. The following query was applied in the databases for the extraction: “concrete mix design” OR “concrete mixture” OR “concrete mix” OR “concrete proportioning” AND (“mathematical programming” OR

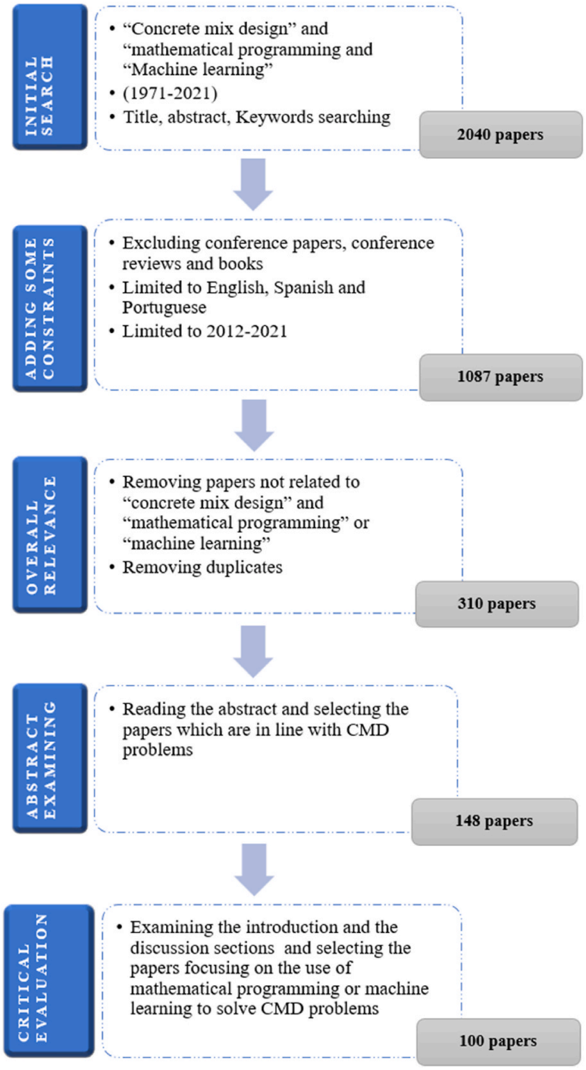

Fig. 2. The procedure of systematic review search.

"mathematical modelling" OR "mathematical modeling" OR "mathematical model" OR "non-linear model" OR "nonlinear model" OR "particle swarm optimisation" OR "particle swarm optimisation" OR "metaheuristic optimisation" OR "metaheuristic optimisation" OR "machine learning" OR "algorithm" OR "genetic algorithm" OR "neural network" OR "support vector machine" OR "regression tree" OR "random forest" OR "linear regression" OR "polynomial regression" OR "support vector regression" OR "gaussian process regression" OR "boosted tree").

Initially, the search based on the abovementioned databases generated a total of 2040 papers. After the first screening, some constraints, such as conference papers, books, language, and a specific timeline period, were applied to the total of registers, which were reduced to 1087 papers after specifying these constraints After evaluating the title and removing the duplicates, the following screening checked the relevance of the remaining documents, which filtered 310 papers. This step mainly focused on selecting the documents linked to solving concrete mix design problems. Next, further examination was performed to guarantee that the scope of the selected papers was aligned with this review by scrutinising their abstracts, which resulted in a set of 148 remaining documents. Then, they were evaluated by thoroughly reading each paper's introduction and discussion sections. The remaining papers were chosen according to the application of mathematical methods and machine learning techniques to find the best composition of the concrete or any optimised property of this composition. Any article that only focused on experiment outcomes and did not solve an optimisation for concrete mix design or predict any concrete property based on its constituents was removed. After the last screening, a total of 100 papers were selected to be evaluated in this review. To summarise the systematic review procedure, Fig. 2 describes each step adopted in this review.

3.2. *Descriptive analysis*

The selected articles were first evaluated according to the year of publication. Then, Fig. 3 was elaborated to reveal the publication rate trend considering the ten years considered in this analysis. It is noticeable that the number of papers related to concrete mix design has continuously risen over the years. Despite being a common topic, this growth can be explained by the different types of concrete studied and several possibilities of the concrete mixture composition aligned with the development of computational techniques. In addition, the search for more sustainable building materials that promote less environmental impact and greater thermal comfort has also stimulated this growth.

Following, the publishing journals most adopted to submit papers regarding concrete mix design were evaluated. Table 1 displays the spread of papers analysed across the publishing journals, bringing 100 documents from 40 different journals. Although there is a wide variety of publishing journals, the Construction and building materials journal contains the most significant publications involving concrete mix design problems, followed by the Journal of Building Engineering and the Journal of Cleaner Production.

Depending on the uses of concrete, a huge variety of concrete can be designed for different objectives, such as high-rise buildings, sustainable buildings, economic buildings, residential buildings, and pavements. As previously described, concrete comprises cement, water, and solid aggregates. However, different materials can be added to this mixture to impart a specific property. Currently, there is a growing demand for building materials with higher performance, more sustainable, and less harmful to the environment. As a result, there is a great deal of adding other materials or partially replacing the cement, which is responsible for emitting significant portions of CO_2 into the atmosphere.

Therefore, the design of concrete mixes is a powerful assistant in specifying the composition of the constituent materials to achieve a specific characteristic. Each concrete mixture design will depend exclusively on the objectives to be achieved in the fresh and hardened states of concrete specified by the designers. Among the papers selected for this review, it was found that there are two well-defined research lines. The first research line is characterised by predicting a specific property of the concrete that one wishes to obtain from the composition of the constituents or a combination of the composition with other properties. While the second research line brings optimisation of the concrete mix design problem, where one or more objectives are selected to be minimised or maximised and thus obtain the optimum concrete mix for each case studied.

Fig. 4 breaks down these two lines of research into three technique classes most applied in the retrieved papers. The first encompasses machine learning (ML) techniques, the second includes mathematical models (MM), and the third presents a hybrid system (HyS) containing both approaches. Machine learning is the most used method in papers where the properties prediction is sought,

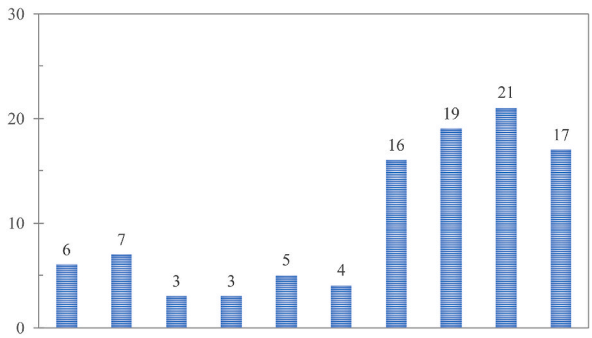

Fig. 3. Distribution of reference papers by year.

Table 1
Distribution of reference papers by publication.

Journal	Number of studies
Construction and Building Materials	35
Journal of Building Engineering	7
Journal of Cleaner Production	6
Cement and Concrete Research	3
Cement and Concrete Composites	3
Sustainability	3
ACI Materials Journal	3
Applied Sciences	2
Computers and Concrete	2
Frontiers in Materials	2
Frontiers of Structural and Civil Engineering	2
Advances in Civil Engineering	2
European Journal of Environmental and Civil Engineering	2
Materials	2
International Journal of Concrete Structures and Materials	1
Automation in Construction	1
Journal of the International Measurement Confederation	1
Neural Computing and Applications	1
Advanced Engineering Informatics	1
Advances in Engineering Software	1
Advances in Materials Science and Engineering	1
Alexandria Engineering Journal	1
Arabian Journal for Science and Engineering	1
Engineering with Computers	1
Expert Systems with Applications	1
Heat and Mass Transfer	1
Heliyon	1
International Journal of Industrial Engineering: Theory Applications and Practice	1
International Journal of Pavement Research and Technology	1
Journal of Computing in Civil Engineering	1
Journal of Construction Engineering and Management	1
Journal of Materials Research and Technology	1
KSCE Journal of Civil Engineering	1
Measurement	1
Polymers	1
Renewable and Sustainable Energy Reviews	1
Resources, Conservation and Recycling	1
Science of The Total Environment	1
Soft Computing	1
Structural Concrete	1

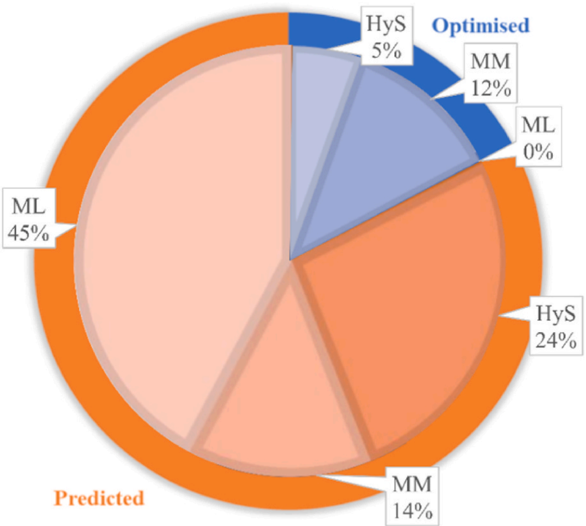

Fig. 4. Papers distribution according to the research line.

appearing in 45% of documents. Then comes hybrid systems with 24% and mathematical models with 14%. However, when the main objective is optimisation, there is an inversion of the techniques used. Mathematical models appear as the most applied tool with 12%, followed by hybrid systems with 5%. It is worth mentioning that there is no document in optimisation research presenting machine learning as the unique technique used.

3.3. *Literature review classification framework*

In this section, a classification framework of the literature review is proposed. The framework classification identifies some categories which characterize the research area examined in the concrete mix design. Besides, each category is mapped to several suitable classes. The main purpose of this framework is to detail the works published in the literature in a consistent and organised way, thus enabling the comprehension of the study and comparisons for future works. Considering the two lines of research found in the literature, the classification of the framework can start from the initial objective of the papers: if it is for the prediction of some property or if it is the optimisation of mixtures with certain minimised or maximised properties. Fig. 5 describes the classification framework broken down into five categories: research line, concrete type, concrete property evaluated, output/objective type of prediction and optimisation cases, and the type of computational aid system used.

The first category of the proposed classification framework is based on the research line adopted in each study. After analysing the selected papers, two specific lines were outlined. One considers the prediction of concrete properties, while the other focuses on optimising the design of concrete mixes. After this indication, one can follow the next step and get into the second category to continue the work classification.

The second category examines the main types of concrete investigated in the literature review. It includes the types most used in the

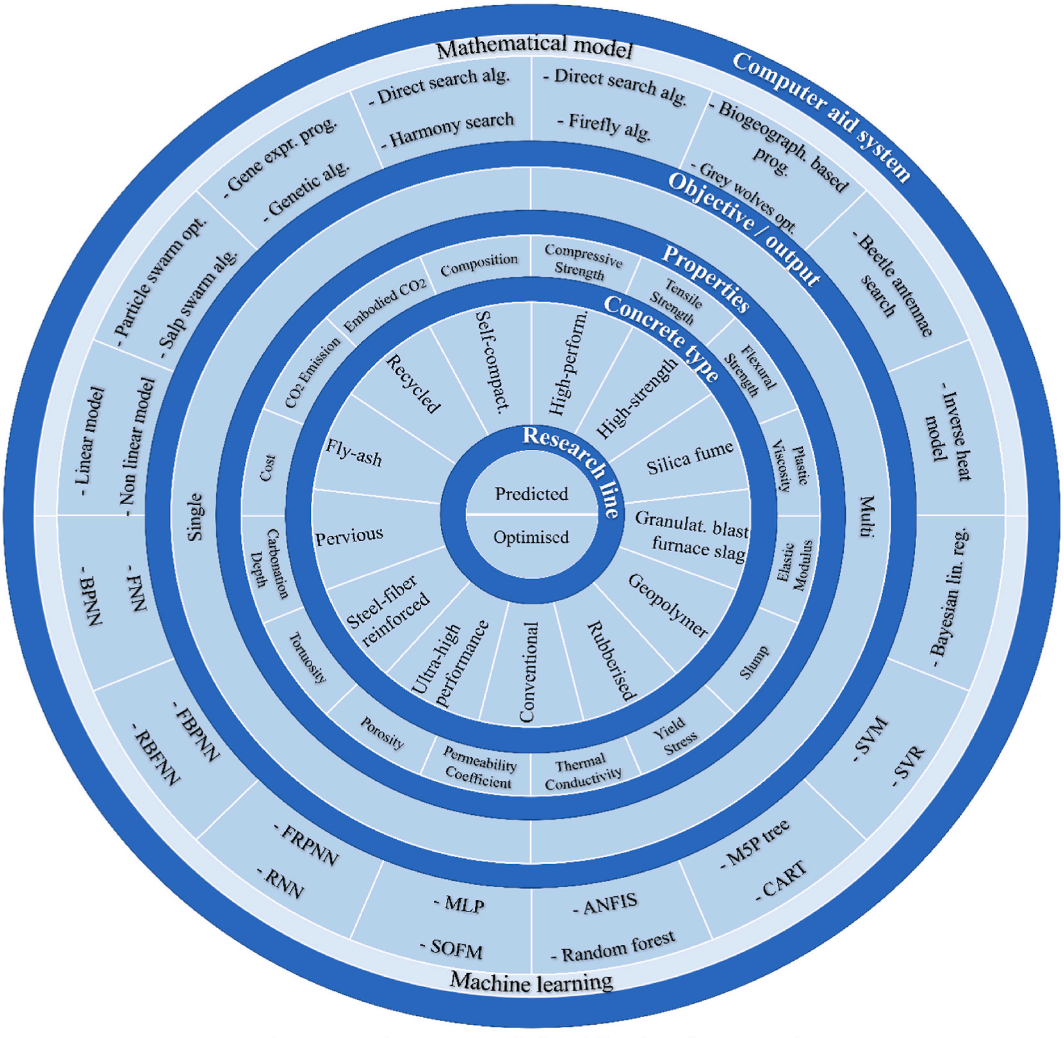

Fig. 5. The proposed classification framework.

construction sector as well as new, more sustainable concretes. Among those evaluated in this review are: conventional concrete, rubberised concrete, recycled aggregate concrete, geopolymer concrete, fly ash concrete, ground granulated blast furnace slag concrete, silica fume concrete, self-compacting concrete, reinforced concrete, high-performance concrete, ultra-high-performance concrete, high-strength concrete, plastic concrete, pervious concrete, oil-palm shell concrete, self-consolidating concrete, pozzolanic concrete, and alkali-activated concrete.

According to the research line adopted, there is a wide variety of properties that researchers seek to predict or optimise. The next category allows the specification of which property is evaluated. Among the properties investigated, several properties are related to the concrete's fresh and hardened state. For example, some works consider slump and slump flow regarding the workability's concrete. Furthermore, many predictions and optimisations of compressive strength, flexural strength, tensile strength, and modulus of elasticity regarding mechanical properties are found in the literature. Besides that, some works evaluate other properties such as cost and sustainability-related properties of the material such as embodied carbon, CO_2 emission, carbonation depth, and thermal conductivity.

The following classification category characterises the output or objective type from each study. Here, it is evaluated if the prediction model output or the optimisation objective considers one or more properties, i.e., single or multi-output/objective. Both research lines present some works predicting or optimising just one property and others considering multiple properties to be predicted or optimised.

The last category considers the applied method to predict the properties or optimise the objective functions. As previously discussed in the introduction section, mathematical programming and machine learning are widely adopted in concrete mix design problems. The main techniques used are artificial neural networks, decision trees, random forest, support vector machine, ANFIS, linear model, non-linear model, particle swarm optimisation, salp swarm algorithm, firefly algorithm, harmony search, and beetle antennae search. Table 2 summarises the technique acronym used in this review.

4. Evaluation of studies

In this section, studies are evaluated based on the proposed classification framework. In the following subsections, the papers selected in this review are organised according to the categories indicated in Fig. 6.

4.1. Review according to the main objective of the work

The first category relies on the primary purpose of the paper. As previously diagnosed, papers addressing the topic of concrete mix design can be primarily classified into two lines of research: prediction and optimisation. According to Fig. 5, the prediction of concrete properties represents most of the studies found in the literature. It reveals that in the analysis carried out on the papers selected, around 83% of the papers take into account the prediction of properties, and only 17% of the documents aim at optimising the concrete mix design problem, minimising or maximising the objective functions. However, some works adopt both research lines, i.e., the same study considers a property prediction and then performs a concrete mix optimisation.

Both research lines have employed machine learning techniques or mathematical models to characterize and analyse concrete mixtures. For instance, Huang et al. [55] followed the prediction line and developed an ANN model to determine the multiple mechanical properties of rubberised concrete based on concrete mix composites. On the other hand, Wang et al. [56] aimed to optimise a

Table 2
List of the techniques acronyms used in this paper.

ABC	Artificial Bee Colony	HS	Harmony Search
ALO	Ant Lion Optimisation	ICA	Imperialist competitive algorithm
ANFIS	Adaptive neuro-fuzzy inference systems	KNN	K-nearest neighbour
ANN	Artificial Neural Network	LCA	Life cycle assessment
BAS	Beetle Antennae Search	LR	Linear regression
BBO	Biogeography-Based Optimisation	LSSVM	Least square support vector machine
BPNN	Back propagation neural network	MARS	Multivariate adaptive regression splines
CART	Classification and regression tree	MEP	Multi-expression programming
CNN	Convolutional neural network	MLP	Multilayer perceptron
DT	Decision Tree	MOLSSVR	Multi-output least squares support vector regression
EA	Evolutionary algorithm	PSO	Particle swarm optimisation
ELM	Extreme Learning Machine	RBFNN	Radial basis function neural network
ESIM	Evolutionary support vector machine inference model	RF	Random forest
FA	Firefly algorithm	RNN	Recurrent neural network
FBPNN	Feed forward back propagation neural network	SLCA	Soccer league competition algorithm
FNN	Feed forward neural network	SOFM	Self-organizing feature map
FRPNN	Feedforward resilient propagation neural network	SQP	Sequential quadratic programming
GA	Genetic algorithm	SSA	Salp swarm algorithm
GEP	Gene expression programming	STR	Smooth Transition Regression
GMDH	Group method of data handling	SVM	Support vector machine
GOA	Grasshopper Optimisation Algorithm	SVR	Support vector regression
GPR	Gaussian process regression	WCA	Water cycle algorithm
GWO	Grey wolves optimisation	wSVM	Weighted support vector machine

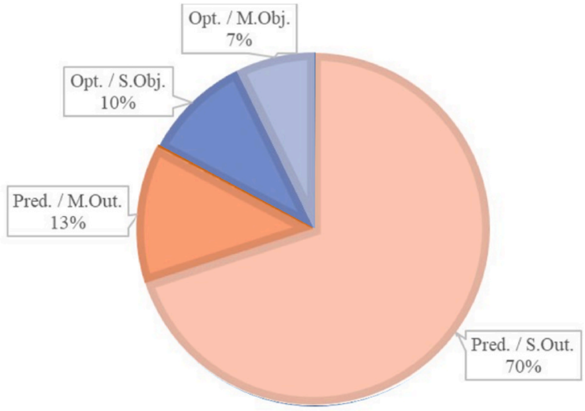

Fig. 6. Number of studies in concrete mix design according to output or objective function type considered.

concrete mixture of slag-blended concrete with minimum CO2 emission. Zhang et al. [20] employed different ML models to predict concrete objectives first. As a second step, the best prediction model was selected as the objective function for the optimisation procedure.

4.2. Studies based on the concrete type

This section focuses on the types of concrete analysed in the retrieved papers. The documents bring up different combinations of concrete constituents that engender a wide variety of concrete types. Therefore, selecting materials and their quantities allows designing concrete with diverse compositions according to the project requirements. Due to this variety, it is possible to notice that studies have evaluated different types of concrete from 2012 to 2021.

Table 3 presents all types of concrete studied in prediction and optimisation research lines. It is worth mentioning that there is a considerable diversity of concrete in both research lines. However, there is a predominance of conventional concrete, concrete containing recycled aggregates, fly ash, silica fume, and slag. These five types of concrete are analysed by 55% and 67% of prediction and optimisation research studies, respectively. Both research lines reveal fly ash concrete as the most studied concrete type. It achieves first place in prediction research and second place in optimisation research.

Although fly ash-blended concrete appears as the most relevant on this list, other types of concrete are also noteworthy, such as plastic concrete and limestone concrete. Furthermore, with the ongoing search for more sustainable materials and mechanical properties similar to conventional concrete, many authors have been investigating new constituents and, thus, new types of concrete. To name a few, Iqbal et al. [57] modelled the mechanical properties of concrete containing waste foundry sand. Besides that, Chung and Tia [58] investigated the effects of cementitious materials on the compressive strength and surface resistivity of limestone concrete

Table 3
Concrete types evaluated in the literature review.

Predicted			
Concrete type	Qt.	Concrete type	Qt.
Concrete containing fly ash	17	Plastic concrete	3
Recycled aggregate concrete	15	High-strength concrete	2
Conventional concrete	12	Ultra-high-performance concrete	2
High-performance concrete	12	Pozzolanic concrete	2
Concrete containing slag	10	Alkali-activated concrete	1
Concrete containing silica fume	8	Waste foundry sand concrete	1
Reinforced concrete	7	Ultra-high-strength concrete	1
Rubberised concrete	5	Pervious concrete	1
Self-compacting concrete	4	Oil palm shell concrete	1
Self-consolidating concrete	4	Hydraulic concrete	1
Geopolymer concrete	3	Lime-stone concrete	1
Optimised			
Concrete type	**Qt.**	**Concrete type**	**Qt.**
Concrete containing slag	6	High-performance concrete	2
Concrete containing fly ash	5	Reinforced concrete	1
Conventional concrete	3	Plastic concrete	1
Concrete containing silica fume	2	Self-compacting concrete	1
Recycled aggregate concrete	2	Pozzolanic concrete	1
High-strength concrete	2	Lime-stone concrete	1

mixes. Zhang et al. [59] inspected the replacement of natural coarse aggregate with oil palm shell and elucidated the pros and cons of oil palm shell concrete.

4.3. Studies based on concrete property

Designing a concrete mixture relies on specifying the properties of the final product and guaranteeing it will meet the property requirements of the project. For this reason, many researchers and designers focus on experiments and mathematical models that better represent the relationship between concrete composition and its properties. Therefore, the third classification category proposed is the concrete property. Table 4 depicts the distribution of the papers according to the main properties predicted and the objectives optimised. Most of the predictions' outputs are related to the mechanical and chemical properties.

Concerning the predicted properties, several papers evaluate the best technique of machine learning and mathematical models to predict concrete properties. Compressive strength is the most investigated property in all studies, representing 43% of the papers evaluated. The predominance in most studies is justified by its importance in the durability design and predicting the service life of concrete structures. Still, regarding the compressive strength, there are some varieties related to the curing time; however, most works try to predict this property after 28 days. Two other highly evaluated properties are elastic modulus and slump, which appear in 9% and 7% of the works. Elastic modulus is another mechanical property that reflects the ability of concrete to deflect elastically. And the slump, related to the fresh concrete state, is a factor that directly contributes to the workability of the mixture. Forecasting the concrete properties, especially the mechanical properties, helps designers in the early characterization of the concrete, thus saving design time.

On the other hand, the papers considering the optimisation process adopt fewer properties as objective functions. Three appear most frequently in single or multi-optimisations among the main properties. 37% of the works look for the optimal concrete mix minimising the cost, 17% look over the compressive strength, and 14% use CO_2 emission as an objective function to minimise. Optimizations, despite being extremely important for the specification of a more suitable concrete mixture for a project, there is still a lack of studies focusing on different objective functions. Most studies still focus exclusively on compressive strength and cost.

4.4. Studies based on objective/output type

The following category breaks down the papers into four main classes. Two classes are associated with the predictive research line, characterised as single and multi-output. While the other two are linked to the optimisation research line, defined as single and multi-objective. The distribution of the studies addressing each of these classes is illustrated in Fig. 6. As is seen from Fig. 6, a prediction with a single output occupies the most significant proportion of studies, with 70% of the studies examined. Another interesting point is that the researchers focus more on single-objective optimisation studies than on multi-objective optimisation, representing only 7% of the documents.

A possible reason for many studies in the prediction area is exploring models more effectively for each type of concrete property. Regarding the optimisation of concrete, the studies related to single optimisation are still more significant than those with multiple

Table 4
Main predicted and optimised properties found in concrete mix design problems.

Predicted			
Properties	Qt.	Properties	Qt.
Compressive strength	66	Permeability coefficient	1
Tensile strength	14	Coefficient of thermal expansion	1
Elastic modulus	13	Modulus of rupture	1
Flexural strength	11	Poisson's ratio	1
Slump	10	Dry shrinkage rate	1
Carbonation depth	4	Shrinkage	1
Mix proportion	4	Porosity	1
Plastic viscosity	3	Transport tortuosity	1
Ultra-pulse velocity	3	Specific heat	1
Thermal conductivity	2	Chloride penetration	1
Slump flow	2	Rapid chloride permeability	1
Interface yield stress	2	Water absorption	1
Autogenous shrinkage	2	GWP	1
Rebound number	1	Fracture energy	1
Embodied carbon	1		
Optimised			
Properties	**Qt.**	**Properties**	**Qt.**
Cost	13	Tensile strength	1
Compressive strength	6	Cracking risk coefficient	1
CO_2 emission	5	Energy consumption	1
Embodied CO_2	2	Resource consumption	1
Slump	2	GHG emission	1
Flexural strength	1	Diffusion coefficient of CO_2	1

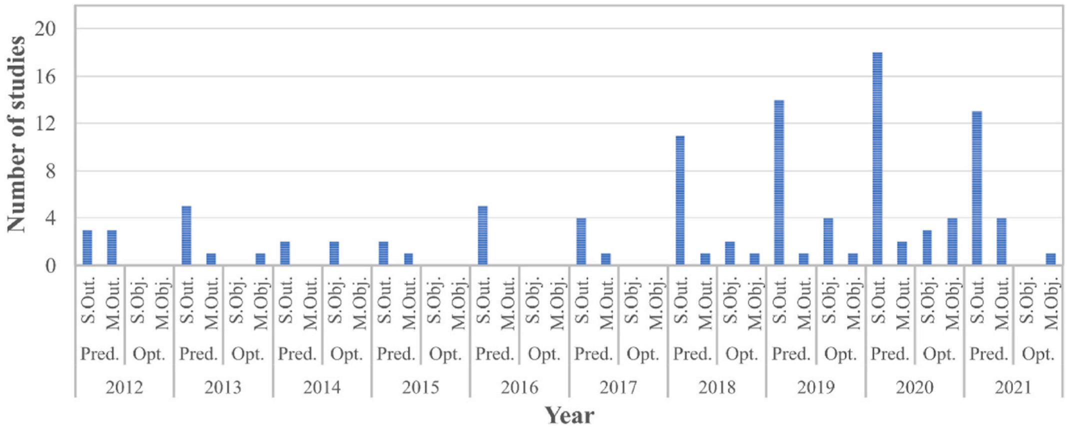

Fig. 7. Studies distribution according to output or objective function type.

objectives. It can also be explained by the effort in optimising different properties simultaneously, where the optimisation of one objective function affects the other's results. Both lines of research indicate the need to be further explored. The first one requires more reliable models for different types of concrete, including all possible constituents that affect the properties of concrete. And the second line should be better explored because the design of concrete mixtures is a trade-off process with few studies published in the literature so far.

Fig. 7 reveals the distribution of these four classes over 2012–2021, which shows the papers according to the output or objective function type. Besides the significant growth in the prediction area of a single property, there is a slight development in single and multi-objective optimisations of concrete properties. Therefore, an increasing trend in the concrete mix optimisation research line is spotted.

4.5. Studies based on computer aid systems adopted

The last classification category takes into account the computer aid system adopted. Based on the selected papers, the works are categorised into three main groups: (1) machine learning techniques, (2) mathematical programming models, and (3) hybrid systems, which englobes the two methods mentioned previously. As seen previously in Fig. 4, machine learning techniques dominate concrete mix design issues accounting for 45% of the studies reviewed. Regarding the mathematical models, the contribution decays to 26% of the papers, and the hybrid system takes 29% of the total concrete mix design studies examined. In order to comprehend the methods used, Fig. 8 breaks down the three groups according to each research line from 2012 to 2021. From 2018 onwards, there has been significant growth in publications in general. Besides the spread of machine learning as the only tool for predicting properties, there is a notable development in adopting the hybrid system to predict properties and optimise the concrete mixture.

(ML – Machine learning, MM – Mathematical model, HyS – Hybrid system).

Further explaining the type of each technique of machine learning and mathematical models, Table 5 brings together the techniques of each method grouped by similar tools and algorithms used in the selected papers. Since the adopted approach to designing a

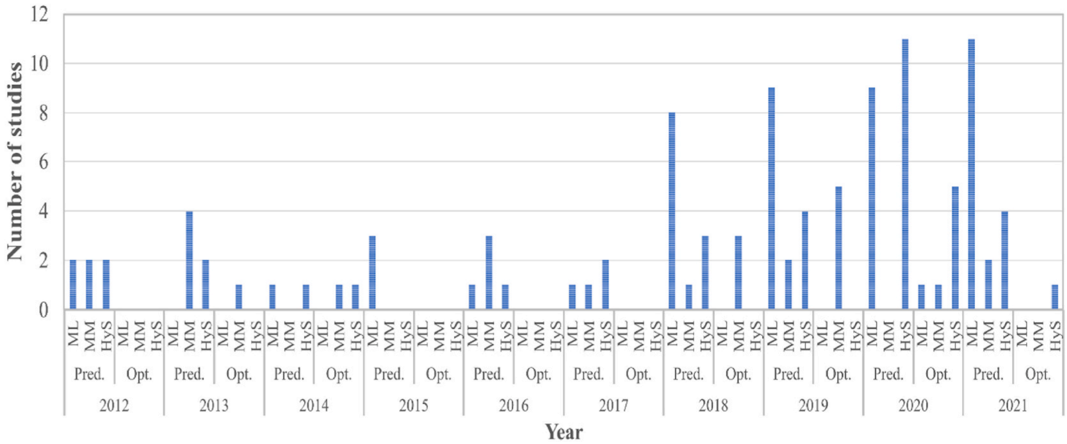

Fig. 8. Studies distribution considering the techniques adopted.

Table 5
Main techniques applied in prediction and optimisation problems related to concrete mix design.

Predicted				
Machine Learning				
Technique		**Qt.**	**Technique**	**Qt.**
Neural Network	Multilayer perceptron (MLP)	16	Adaptive neuro-fuzzy inference system (ANFIS)	2
	Feed-forward backpropagation (FBPNN)	15	Self-organising feature map (SOFM)	1
	Backpropagation (BPNN)	11	Convolutional neural network (CNN)	1
	Feed-forward (FNN)	9	Extreme learning machine (ELM)	1
	Radial basis function neural network (RBFNN)	3		
Support Vector Machine	Support vector machine (SVM)	14	Evolutionary support vector machine inference model (ESIM)	1
	Support vector regression (SVR)	6	Weighted support vector machine (wSVM)	1
	Least squares support vector machine (LSSVM)	2	Multi-output least squares support vector regression (MOLSSVR)	1
Decision Tree	Random forest (RF)	8	Adaptive boosting algorithm (AdaBoost)	2
	M5P model tree	5	XGboost	1
	Gradient boosting tree	4	Boosting Smooth Transition regression trees (BooST)	1
	Regression tree	3	Chi-squared automatic interaction detector (CHAID)	1
	Decision tree	2		
Linear Regression	Multivariate adaptive regression splines (MARS)	5	Ridge regression	2
	Linear regression (LR)	4	Lasso regression	1
Non-linear Regression	Gaussian process regression (GPR)	4	Minimax probability machine regression	1
	K-nearest neighbour (KNN)	2	Non-linear regression	1
Logistic Regression	Multilogistic regression	1		
Mathematical Optimisation				
Metaheuristic Method	Genetic algorithm (GA)	12	Soccer league competition algorithm (SLCA)	1
	Particle swarm optimisation (PSO)	4	Group method of data handling (GMDH)	1
	Gene expression programming (GEP)	4	Ant lion optimisation (ALO)	1
	Firefly algorithm	3	Deep learning	1
	Beetle antennae search	3	Grasshopper optimisation algorithm (GOA)	1
	Genetic programming	3	Grey system theory	1
	Biogeography-based optimisation (BBO)	2	Direct search optimisation algorithm	1
	L-SHADE	1	Artificial bee colony algorithm (ABC)	1
	Imperialist competitive algorithm (ICA)	1	Grey Wolves Optimisation	1
	Multi-expression programming (MEP)	1	Mixed regression model	1
	Salp swarm optimisation	1	Harmony search	1
	Water cycle algorithm (WCA)	1		
Exact Method	Linear model/regression	5	Semi-empirical model based on Fick's law	1
	Non-linear model	3	Model-based on Abram's law	1
	Life cycle assessment	2	Densified mixture design algorithm	1
	Hydration model	1	Principal component analysis (PCA)	1
	Carbonation reaction model	1		
Heuristic Method	Five-layer fuzzy inference system	1	Fuzzy logic	1
	Fuzzy TSK	1		
Optimised				
Machine Learning				
Technique		**Qt.**	**Technique**	**Qt.**
Neural Network	Backpropagation (BPNN)	3	-	
Decision Tree	Random forest	2	Gradient boosting tree	1

(continued on next page)

Table 5 (*continued*)

	Support Vector Machine (SVM)	Support vector regression (SVR)	1	Evolutionary support vector machine inference model (ESIM)	1
Mathematical Optimisation					
	Exact Method	Polynomial model	15	Sequential quadratic programming	1
		Life cycle assessment (LCA)	1	Adaptive surrogate model	1
	Metaheuristic Method	Genetic algorithm (GA)	8	Beetle antennae search (BAS)	1
		Firefly algorithm (FA)	2	Biogeography-based optimisation (BBO)	1
		Gene expression programming (GEP)	2	Water cycle algorithm (WCA)	1
		Particle swarm optimisation (PSO)	2	Evolutionary algorithm (EA)	1

concrete mixture depends on the research line and the properties chosen to be predicted or optimised, Table 4 is divided into two parts. The first part quantifies machine learning and mathematical models used to predict concrete properties, while the second part shows the techniques applied to optimise the concrete mixture.

Considering the prediction research line and the application of machine learning techniques, the first part of Table 5 shows that ANN covers most studies related to the properties prediction. They are responsible for 30% of the total works in this research line. Then, the two machine learning techniques most applied to determine concrete properties are DT and SVM with 14% and 13%, respectively. Among these three main groups, the most common techniques adopted are multilayer perceptron, feed-forward neural network, backpropagation neural network, random forest, and support vector machine. In order to evaluate the technique most adequate that generates the most reliable response, many works use a comparative methodology between the techniques. Therefore, more than one approach is used to predict the concrete properties, which allows the authors to select the technique with a minor error.

Regarding the mathematical models in the prediction line, metaheuristic methods have been gaining prominence and appear in 24% of the works, followed by exact methods with 8% and only 2% of heuristic methods. Among the main techniques, GA is the one that appears most frequently in the evaluated studies. In fewer studies, other techniques implemented are PSO, GEP, linear models, and non-linear models. Part of these mathematical algorithms in this research line is employed to tune the machine learning technique's hyperparameters and improve the property prediction.

The second part of Table 5 indicates a reduction in machine learning techniques compared to other lines of research. Techniques of machine learning groups account for only 7% for ANN, 7% for DT, and 5% for SVM of studies related to optimisation. On the other hand, exact and heuristic methods significantly increase, representing 18% and 18% of the total techniques used in this optimisation line. The approaches adopted are the polynomial model, GA, FA, GEP, and PSO. It is worth remembering that some techniques used to predict properties are used to formulate the objective functions to optimise concrete mixtures.

The proposed classification framework intends to guide researchers through the published works on concrete mix design and recognize patterns in each research line. Consequently, it is possible to clearly and quickly understand the main points covered in each work through the five categories adopted.

It is possible to visualise specific patterns of the prediction models if we evaluate the most common outputs in this systematic review, such as compressive strength, tensile strength, elastic modulus, and flexural strength. For example, regarding the compressive strength, although there is an additional feature related to the curing time, it is used in the same models. The most used models are artificial neural networks, random forests, support vector machines, and some metaheuristic methods. Considering the tensile strength, the elastic modulus, and flexural strength as the output, most works employ an artificial neural network model to predict these properties.

Another possible category not included in the classification framework is the input variables due to their dependency on the output property and the type of concrete. For instance, considering the compressive strength, the model could consider as input variables cement, blast-furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate [20]. While Zhang et al. [60] also considered the maximum size of coarse aggregate and curing age. Moon et al. [61] used different input variables: cement, coarse aggregate, sand, water, fineness modulus, and 3-day concrete strength. If we consider another property, such as thermal conductivity or permeability coefficient, the input variables would be quite distinct from the ones presented above. For the first property, the input can be, and for the second one, the water-to-cement ratio, aggregate-to-cement ratio, and aggregate size [50]. Due to this great diversity, this work designed the framework with only five categories and did not include the input variables.

Besides that, it is possible to broadly examine the evolution of research in concrete mix design. Table 6 summarises each of the documents selected in this review and briefly details the five categories of this framework.

5. Discussion

In this discussion section, the papers analysed through the classification framework developed in Section 3 answer the main research questions addressed in this review.

1. What are the main machine learning algorithms that have been used in order to come up with the concrete mix design?

After analysing the selected papers, six main groups are observed when it comes to machine learning techniques applied to concrete mix design: artificial neural networks, decision trees, support vector machines, linear regression, non-linear regression, and logistic

Table 6
Description of the papers examined.

N	Year	Description	Ref
1	2021	Developed a prior information-based NN model to obtain a 28-day concrete strength prediction model of conventional concrete.	[61]
2	2021	Proposed a hybrid model based on SVR and L-SHADE to predict the plastic viscosity of conventional concrete.	[62]
3	2021	Provided a multi-objective optimisation model using BPNN and beetle antennae search algorithm to maximise compressive strength and minimise cost and embodied CO_2 of silica fume concrete.	[60]
4	2021	Applied a predictive model based on BPNN to determine the 28-day concrete strength of geopolymer concrete.	[63]
5	2021	Determined the design relationship between various concrete mix composites of rubberised concrete and their multiple mechanical properties (7-d compressive strength, 28-d compressive strength, flexural strength, tensile strength, and elastic modulus) simultaneously.	[55]
6	2021	Determined a multilayer perceptron model with the highest prediction accuracy to predict the thermal conductivity of concrete containing fly ash, slag, and recycled aggregates.	[30]
7	2021	Compared self-organizing feature map (SOFM) and multilayer perceptron to predict the compressive strength of slag concrete in early ages and more extended periods, with only three parameters as input variables.	[43]
8	2021	Established a prediction model based on the extreme learning machine to simultaneously predict rubberised concrete's 28-day compressive strength, splitting tensile, and flexural strength.	[42]
9	2021	Proposed a hybrid model using radial basis function neural network (RBFNN) and firefly optimisation algorithm (FOA) to predict the compressive strength of self-compacting concrete.	[28]
10	2021	Applied two machine learning methods (BPNN and SVM) to estimate the compressive strength of recycled aggregate concrete.	[47]
11	2021	Presented an RF model to predict two properties of fly ash-based alkali-activated concrete – slump flow and compressive strength.	[51]
12	2021	FBPNN was applied to predict a multi-output response (compressive strength, rebound hammer number, and ultrasonic pulse velocity) of sustainable concrete containing various amounts of fly ash, silica fume, and blast furnace slag.	[64]
13	2021	Different technical approaches (Linear, non-linear regressions, multi-logistic regression, M5P-tree, and FNN) were used and compared to predict the compressive strength of high-volume fly ash concrete.	[13]
14	2021	It was researched to develop an optimum machine learning algorithm for predicting steel fibre-reinforced concrete's compressive and flexural strengths. The linear regressor, lasso regressor, ridge regressor, K-nearest neighbour (KNN) regressor, decision tree regressor, random forest regressor, AdaBoost regressor, gradient boost regressor, and XGBoost regressor were used for machine-learning models.	[65]
15	2021	Imperialist Competitive Algorithm (ICA) was employed to develop new formulas to predict the tensile, compressive, and flexural strengths of recycled coarse aggregate concrete based on water, cement, RCA, natural coarse aggregates, and natural fine aggregates content.	[66]
16	2021	Development of Multi-Expression Programming (MEP) model to predict the split tensile strength and modulus of elasticity of concrete containing waste foundry sand.	[57]
17	2021	Implemented a hybrid ensemble model to predict the compressive strength of concrete containing fly ash and blast furnace slag. The predicted outputs of four conventional machine learning models (FNN, Linear and Non-Linear Multivariate Adaptive Regression Splines (MARS-L and MARS-C), Gaussian Process Regression (GPR), and Minimax Probability Machine Regression (MPMR)) were combined and trained using ANN to construct the hybrid model.	[67]
18	2020	A hybrid predicted model comprising an SVR model and FA was applied to predict compressive strength and flexural strength for steel fibre reinforced concrete. The FA-SVR model was then used as the objective function for a developed multi-objective optimisation to find the optimal concrete mixture proportion.	[68]
19	2020	Compared some hybrid models (BPNN-FA. SVM-FA, RF-FA) to predict compressive strength and tensile strength, then selected the best model to introduce it in a multi-objective optimisation with compressive strength, tensile strength, cost, and CO_2 emission.	[8]
20	2020	Adopted Boosting Smooth Transition regression trees (BooST) to investigate the predictive performance of Concrete Compressive Strength for high-performance compared with other contemporary methods for higher predictive accuracy.	[14]
21	2020	An optimum design method of high-strength concrete was developed for improving crack resistance based on ANN and GA.	[24]
22	2020	A particle swarm optimisation coupled with gradient boosting regression trees model was developed to optimise the mixture design of recycled aggregate concrete for various compressive strengths.	[29]
23	2020	A four-layer multi-layer-perceptron (MLP) model was developed for forecasting the compressive strength of ultra-high-performance concrete (UHPC) for a given mixture design.	[41]
24	2020	Proposed a multi-objective optimisation method integrating BPNN, RF, and PSO to optimise concrete mixture proportions of plastic concrete and high-performance concrete	[20]
25	2020	Some machine learning techniques (FNN, GPR, SVM, DT, LR) were compared to identify the high-strength concrete mixes while minimising the embodied carbon value of that mix composition.	[48]
26	2020	Predicted permeability and compressive strength of pervious concrete by applying multi-output least squares support vector regression (MOLSSVR) coupled with beetle- antennae search (BAS) algorithm.	[50]
27	2020	Estimated the compressive strength of the concretes containing blast furnace slag using a hybrid system composed of FBPNN and a multi-objective salp swarm algorithm.	[26]
28	2020	A hybrid artificial intelligence model based on RF and beetle antennae search (BAS) was proposed to predict the compressive strength of oil palm shell concrete.	[59]
29	2020	The water cycle algorithm, soccer league competition algorithm, GA, FNN, and SVR were applied in order to predict the compressive strength. Then, the most efficient sustainable objective function was used to estimate the mixture design of sustainable concrete.	[6]
30	2020	Presented an ensemble machine learning model (RF and SVM) to predict the modulus of elasticity (MOE) of concrete formulated using recycled concrete aggregate.	[52]
31	2020	A hybrid method using LSSVM and PSO was proposed for predicting interface yield stress and the plastic viscosity of conventional concrete mixes.	[31]
32	2020	A genetic algorithm was used to find the optimal mixture design of fly ash and slag ternary blended concrete, considering the costs of CO_2 emissions and material as objective functions.	[69]
33	2020	The AdaBoost algorithm is adopted to predict the compressive strength of concrete containing fly ash and slag.	[54]
34	2020	Estimated and compared the compressive strength of plastic concrete using four computational intelligence, including SVM, GMDH, and multi-gene genetic programming (MGGP).	[70]
35	2020	The strength characteristics of geopolymer self-compacting concrete with GEP were modelled to perform a single output response and the artificial neural networks FBPNN to predict the properties simultaneously.	[25]

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Table 6 (*continued*)

N	Year	Description	Ref
36	2020	Four analytical models were built based on FBPNN, to predict the 1-day, 7-day, and 28-day compressive strengths and slump flow of ultra-high-performance concrete.	[71]
37	2020	Investigated an ensemble approach composed of MARS and GBM to predict high-performance concrete's concrete strength.	[72]
38	2020	ANFIS models were developed to predict the compressive strength of rubberised concrete.	[73]
39	2019	A slag concrete with low CO_2 emissions was designed using GA.	[56]
40	2019	A concrete mix design for low-CO_2 fly ash concrete considering climate change, carbonation, and CO_2 uptake was presented.	[74]
41	2019	It was investigated the efficiency of ALO for fine-tuning an MLP neural network in the field of concrete slump prediction and compared it with other benchmark models (BBO and GOA).	[22]
42	2019	Used a GA to search for the optimal mixture of high-strength concrete, considering the sum of the material cost and the cost of CO2 emissions as the optimisation objective of the GA.	[75]
43	2019	Predicted the relative viscosity, yield stress, and slump flow of self-consolidating concrete employing an FBPNN to predict the rheological properties under hot weather conditions and prolonged mixing.	[76]
44	2019	Linear regression and random forest were applied to predict the coefficient of thermal expansion of conventional concrete.	[77]
45	2019	Three soft computing methods of FBPNN, MARS, and M5Tree were employed to predict plastic concrete's slump, compressive strength, and elastic modulus.	[78]
46	2019	FNN, M5P model tree and RF techniques were used to predict the mechanical performance of recycled aggregate concrete containing mineral admixtures.	[79]
47	2019	Used a mathematical approach, namely Grey System Theory (GST), to examine the parametric sensitivity of the mechanical properties of recycled aggregate concrete. Then, a Multiple Nonlinear Regression (MNR) and BPNN simulated the mechanical properties.	[80]
48	2019	Four data mining models (Bayesian Ridge model, Gaussian Process, Regression Tree, and Gradient Boosting Regression Tree) were compared to predict hydraulic concrete's mechanical properties.	[81]
49	2019	A hybrid system composed of three neural networks and GA was proposed to predict the transport tortuosity of the pore system of fly ash concrete.	[82]
50	2019	A method based on the inverse heat transfer problem through a direct search optimisation algorithm was developed to predict the heat of cement hydration, thermal conductivity, and specific heat.	[27]
51	2019	A multi-island GA method was combined with an adaptive surrogate modelling approach to achieve an optimal concrete mixture of fly ash and phosphorous slag concrete by optimising CO2 emissions and cost.	[83]
52	2019	Examination of an FNN model combined with an artificial bee colony (ABC) algorithm in predicting chloride penetration in self-consolidating concretes.	[23]
53	2019	Applied FNN to predict the compressive strength of waste rubber concrete.	[84]
54	2019	Applied MLP to predict the carbonation of fly-ash concrete, taking into account the most influential parameters, including mixture proportions and exposure conditions.	[40]
55	2019	Used BBP to predict the compressive strength of silica fume concrete, while constrained biogeography-based optimisation (CBBO) was used to estimate its optimal mix design minimising cost.	[85]
56	2019	An MLP model was applied to investigate the modulus of elasticity of recycled aggregate concrete.	[86]
57	2019	Compared an MLP technique using four different training algorithms in steel fiber reinforced concrete to predict water absorption, compressive strength, flexural strength, split tensile strength, and slump.	[87]
58	2018	MARS, M5P Tree, LS-SVM, MLP, and Multiple Linear Regression (MLR) were employed to compare the prediction of compressive strength and ultrasonic pulse velocity of fiber reinforced concrete.	[88]
59	2018	A multi-objective Grey Wolves Optimisation (GWO) was applied to find a simple FNN model with acceptable error to predict the compressive strength of silica fume concrete.	[89]
60	2018	BPNN was used to analyse the significance of each aggregate characteristic and determine the best combinations of factors that would affect the compressive strength and elastic modulus of recycled aggregate concrete.	[90]
61	2018	An MLP model was designed to investigate the effect of concrete mix compositions, weathering effect, and exposure time on carbonation depth in concrete.	[91]
62	2018	Non-linear and mixed regression analyses were applied to model the compressive strength of limestone and fly ash concrete.	[15]
63	2018	Sequential quadratic programming was employed to solve the optimal mix design problem of self-compacting concrete in order to minimise the concrete cost.	[16]
64	2018	Mathematical models were developed to perform optimisation of GHG emissions for four groups of concrete containing fly ash, ground granulated blast furnace slag, natural pozzolans, and limestone.	[18]
65	2018	BPNN, fuzzy TSK, SVR, and RBFNN compared the elastic modulus of recycled aggregate concrete.	[92]
66	2018	BPNN was employed to establish the prediction models of compressive strength and the slump of the pozzolanic concrete.	[93]
67	2018	Used FBPNN and SVM to estimate the compressive strength and flexural strength of carbon-fiber-reinforced lightweight concrete exposed to high temperatures.	[94]
68	2018	Applied gene expression models to predict slump flow and compressive strength of normal weight concrete containing granule blast furnace slag.	[95]
69	2018	A system based on an FNN model integrated with a modified firefly algorithm (MFA) was developed to predict high-performance concrete's compressive and tensile strength.	[96]
70	2018	Predicted the compressive strength of recycled concrete using a Convolutional Neural Network (CNN).	[97]
71	2018	A Multivariate Adaptive Regression Spline (MARS) model was designed to predict the compressive strength of fly ash-based geopolymer concrete.	[98]
72	2018	The recycled aggregate concrete's compressive strength was predicted by using FBPNN.	[99]
73	2017	Two BPNN were developed to predict the ingredients of self-compacting concrete, one to foresee all of them in one step and the other to predict one component per step.	[100]
74	2017	A GA was applied to optimise the connection weights for each MLP model neuron to predict the compressive strength of pozzolanic concrete.	[101]
75	2017	Three different models of MLR, BPNN, and ANFIS were compared in order to predict the compressive strength of concrete.	[102]
76	2017	Gene expression programming (GEP) was employed to predict the compressive strength, elastic modulus, flexural strength, and splitting tensile strength of recycled aggregate concrete.	[103]

(*continued on next page*)

Table 6 (*continued*)

N	Year	Description	Ref
77	2016	Proposed a model for predicting compressive strength and global warming potential (GWP) for concretes containing fly ash and blast furnace slag.	[17]
78	2016	Integrated PSO and MLP to predict compressive strength, splitting tensile strength, fracture energy, and flexural strength of self-compacting concrete.	[7]
79	2016	An SVM model was proposed for the autogenous shrinkage prediction of concrete mixtures.	[49]
80	2016	A numerical procedure consisting of a blended hydration model and a carbonation reaction model was presented to evaluate slag concrete's compressive strength and carbonation depth.	[104]
81	2016	A new meta-model was developed to calculate the carbonation front depth of reinforced concrete based on the analytic solution of Fick's first law.	[105]
82	2015	Applied FBPNN to predict the concrete mix composition for steel fiber-reinforced concrete.	[106]
83	2015	Employed a M5′ model tree algorithm to predict the elastic modulus of recycled aggregate concrete.	[107]
84	2015	A prediction model through FBPNN was developed to predict concrete shrinkage containing silica fume and fly ash.	[108]
85	2014	Evolutionary Support Vector Machine Inference Model (ESIM) predicted the compressive strength of high-performance concrete and integrated ESIM and GA to optimise concrete mixtures.	[109]
86	2014	A numerical technique was developed to obtain optimum concrete mix proportions through a genetic algorithm (GA) for reinforced concrete structures under carbonation.	[110]
87	2014	Individual and ensemble learning classifiers with MLP, SVM, CART, and LR were constructed to predict the compressive strength of high-performance concrete.	[111]
88	2013	A five-layer fuzzy inference system (FIS) was designed to estimate the quantities of concrete ingredients based on the American Concrete Institute (ACI) method of concrete mixture design.	[112]
89	2013	The densified mixture design algorithm (DMDA) was applied in the concrete mix design of self-consolidating concrete to evaluate the effect of the paste amount on the slump, slump flow, compressive strength, and ultrasonic pulse velocity.	[113]
90	2013	Compared linear regression, non-linear regression, and FBPNN models to predict rapid chloride permeability of self-consolidating concretes based on their mixture proportions.	[114]
91	2013	Employed an evolutionary algorithm (EA) to minimise CO2 emission and cost of concrete containing fly ash and slag.	[115]
92	2013	Prediction of compressive strength of concretes containing silica fume and styrene-butadiene rubber with a mathematical model based on Abrams' law.	[116]
93	2013	The compressive strength of high performance concrete was predicted using genetic programming.	[117]
94	2013	The compressive strength of high performance concrete was predicted using individual and ensemble models composed of SVM, MLP, CART, CHAID, LR, and GENLIN.	[5]
95	2012	The HS algorithm was applied to estimate the mix proportion of high-performance concrete.	[21]
96	2012	Proposed an FBPNN model for predicting the early-age autogenous shrinkage of concrete containing silica fume and fly ash.	[118]
97	2012	Used RBFNN to predict yield stress and plastic viscosity and optimise the mix proportioning for high-performance concrete.	[119]
98	2012	Combined an MLP model with Principal Component Analysis (PCA) and developed six neural networks models for predicting slump and compressive strength in concrete with mineral additives such as blast furnace slag, fly ash, and silica fume.	[120]
99	2012	A hybrid system to predict high-performance concrete compressive strength was proposed integrating Fuzzy Logic (FL), weighted Support Vector Machines (wSVM) and fast messy genetic algorithms (fmGA).	[121]
100	2012	Utilized gene expression programming (GEP) to derive a new model for predicting the compressive strength of high performance concrete mixes.	[122]

regression. A predominance of the first three groups can be observed in the papers reviewed. In most documents, artificial neural networks have been used in several algorithms (feed-forward neural network, backpropagation neural network, multilayer perceptron) for property predictions and even used as objective functions for optimisation problems. However, despite the widespread use of this technique for predicting compressive strength at different concrete ages, it is also applied to predict other properties such as tensile strength, elastic modulus, slump, and carbonation depth.

Support Vector Machines (SVM) and Decisions Trees (DT) have also gained prominence in predicting concrete mixture properties, especially support vector regression, random forest, and M5P model trees. However, some studies reveal that in multi-output prediction, a model can have higher accuracy than others, depending on the property to be predicted. For example, the backpropagation neural network algorithm can achieve superior performance in predicting the compressive strength of concrete. At the same time, RF can provide greater accuracy in predicting properties such as slump [20]. Some comparative studies between the three types of machine learning show that ANN performed considerably better in predicting mechanical properties, such as compressive strength, followed by RF and M5P model tree [79].

Although ANN, SVM, and DT present excellent results in predicting properties, comparative studies between machine learning techniques indicate the superiority of other less explored ones. For example, the Multivariate Adaptive Regression Splines (MARS) technique was compared to the multilayer perceptron and least square support vector machine and performed better compared to these other techniques in predicting compressive strength and ultrasonic pulse velocity [88]. However, notwithstanding the promising results, this technique appears in only five studies.

Besides that, some studies focus on building a computational ensemble model consisting of a set of machine learning algorithms. Some papers compare the individual machine learning techniques with this ensemble approach, revealing a higher accuracy when employing multiple techniques. Thus, new models can be built by integrating different algorithms, allowing vast possibilities to find more accurate models.

2. What are the mathematical optimisation algorithms that have been used in order to help concrete mix design?

As mentioned in the preceding section, mathematical models are often used in concrete mix design to obtain the best concrete composition that meets some objective functions. According to each study, these functions are specified and aim at minimising or maximising some characteristics of the concrete. Different properties are used as objective functions; compressive strength and cost are the most evaluated.

Among the algorithms used in the 2012–2021 period, the Genetic Algorithm (GA) is the optimisation algorithm most widely adopted since the beginning of the period evaluated. However, all the articles selected for this review employed single-objective optimisations to find the best composition varying the objective functions. For instance, Kwon et al. [110] obtained optimum concrete mix proportions through GA using the diffusion coefficient of CO_2 as an objective function for reinforced concrete structures.

Other algorithms also appear with a particular frequency in concrete proportioning studies. For example, the Firefly Algorithm (FA) has been frequently used in multiobjective optimisations with compressive strength, cost, and CO2 emissions as objective functions [8]. Another example is Gene Expression Programming (GEP) is applied in single-objective optimisation minimising cost [75] and multiobjective optimisation, evaluating compressive strength and slump [96]. Particle Swarm Optimisation (PSO) is also used in both types of optimisation, which is analysed the cost for the single case [29] and compressive strength, cost, and slump for the multi-objective analysis [20].

Another application of mathematical models is optimising other techniques' hyperparameters and increasing the model's accuracy [82]. These four algorithms also appear frequently in optimising hyperparameters; however, GA is the most relevant in this algorithm optimisation application.

3. How is the literature linking both aspects, mathematical optimisation and machine learning, in order to design a concrete mix?

Based on the reviewed papers, a classification framework was proposed, noting the existence of two well-defined lines of research for the concrete mix design project.

The first line of research is linked to the optimisation process of concrete mixtures. Through mathematical models, objective functions that must be maximised or minimised are represented to obtain the best composition according to the project objective. The studies analysed showed mathematical models optimising the concrete mix design.

The second line is related to the prediction of concrete properties. In this line, most of the researchers found in the literature are concentrated, and about 83% of the works in this area use machine learning to predict concrete mixtures' characteristics.

Many studies have also adopted hybrid models in optimisation and prediction research lines. The former uses machine learning techniques to represent some properties as an objective function. For example, the application of BPNN represents the compressive strength and slump as objective functions. Then, a particle swarm algorithm is applied to perform a multi-objective optimisation [20]. The latter uses mathematical models to improve the machine learning techniques' parameters and thus optimise the model [50].

6. Conclusions

Operational research techniques for concrete mix design have been used to improve the results achieved by the conventional concrete mix proportioning methods based on many experimental tests. Mathematical programming and machine learning methods applied in concrete mix design have turned attractive for several reasons. To begin with, the different composition combinations due to the diversity of raw materials make the concrete design very challenging to perform all laboratory experiments. In addition, laboratory methods are massive, time-consuming, and do not guarantee an ideal concrete mixing solution. Furthermore, mathematical models and machine learning techniques innovate the concrete design method, ensuring that concrete prediction and optimisation models are carried out quickly and accurately.

This review gathered the most relevant papers on concrete mix design from 2012 to 2021. And then, it was proposed a classification framework that could group the works into different categories. Within the analysis of 100 studies, the framework was broken down into five main categories: type of research line, type of concrete, concrete properties, type of output or objective, and type of computer aid system adopted.

In order to focus on the most important and relevant papers, this systematic review was subjected to some constraints to select them. The main limitations of this work were databases and the boundary definition, which took into account only papers published from a specific timeline, written in English, and did not include any conference paper. Another limitation was regarding the design of the classificational framework, which could have included a variety of input variables. However, the inclusion of this category would be challenging to group in a single category since the input variables depend on the output to be predicted. For those reasons, the classification framework focused on these five categories. According to the reviewed papers, two research lines were spotted. Around 83% are mainly aimed at predicting the properties of concrete, where 70% developed a prediction model with a single output response, and 13% presented a model with multi-property prediction. The remaining documents, around 17%, look for optimising the concrete mixture, with 10% showing a single objective optimisation and 7% minimising or maximising multi-objective functions.

Among the types of concrete investigated, there is a growing trend of studies in both research lines with concrete containing recycled aggregate and supplementary cementitious material such as fly ash, slag, and silica fume. It can be justified by encouraging the reuse of wasted materials and developing more sustainable materials. Regarding the properties predicted or used as objective functions, mechanical properties are the most evaluated, especially compressive strength. Another objective function often used is cost, which is always considered in optimisation studies. These two properties are presented in 60% and 37% of the examined research lines.

Furthermore, the framework was broken down into three classes to evaluate the computer aid system: mathematical models, machine learning, and hybrid system. Most works applied machine learning to predict some concrete property when it comes to predicting research. About 45% of all documents use at least one machine learning technique. Mathematical models and hybrid systems are used in both research lines, the former accounting for 26% and the latter for 29% of the articles. Although several techniques have been used in both areas, a relevant domain of artificial neural networks, support vector machines, decision trees, and genetic algorithms was noted.

Although this subject presents many relevant works for predicting properties and optimising concrete mixtures, few focus on multi-objective optimisation. Since several objective functions can show a trade-off relationship, simultaneously optimising them is pretty challenging. Therefore, in order to simplify the mathematical optimisation model, most studies use only a single objective function. However, multi-objective optimisation can adequately represent the concrete mix problem, making it more reliable. Accordingly, future works could focus on multi-objective optimisations, analysing different properties so that the results encompass several concrete characteristics, for example, compressive strength, cost, CO_2 emission, and thermal conductivity. Thus, it can achieve a more resistant, less costly, and more sustainable concrete material.

Author contribution statement

Ana Carolina Rosa, Ahmed W. A. Hammad, Dieter Boer, Assed N. Haddad: conceived and designed the analysis; analysed and interpreted the data; contributed analysis tools or data; wrote the paper.

Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

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