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Anerdi Costanza[1], Jonathan Melchiorre[2], Vincenzo Randazzo[3], and Giuseppe C. Marano[2]

[1] Politecnico di Torino, DIMEAS, Dipartimento di Ingegneria Meccanica e Aerospaziale, Corso Duca Degli Abruzzi, 24, Turin 10128, Italy,
Email: costanza.anerdi@polito.it

[2] Politecnico di Torino, DISEG, Dipartimento di Ingegneria Strutturale, Edile e Geotecnica, Corso Duca Degli Abruzzi, 24, Turin 10128, Italy,
Email: jonathan.melchiorre@polito.it, giuseppe.marano@polito.it

[3] Politecnico di Torino, DET, Dipartimento di Elettronica e Telecomunicazioni, Corso Duca Degli Abruzzi, 24, Turin 10128, Italy,
Email: vincenzo.randazzo@polito.it

Abstract. Concrete, as the predominant construction material, plays a vital role in human development. However, its production involves a complex mix of factors, such as the presence of raw materials, hydration reactions, curing conditions and environmental parameters resulting in uncertainties and variations in the final material properties. Achieving desired concrete properties necessitates a deep understanding of these interdependencies and the ability to optimize the mixture accordingly. Furthermore, the growing demand for sustainable and environmentally friendly concrete adds an additional layer of complexity to the production process. Machine learning (ML) has emerged as a transformative tool in concrete research, offering autonomous solutions to complex tasks. To the best of our knowledge, this is one of the first studies to tackle concrete mix design using ML, making the proposed research a frontier one. Different machine learning models were trained on a dataset of 1100 experimentally tested concrete samples to define the consistency class and the compressive strength of concrete mixtures on the basis of the mix design components. The results indicated that the proposed approach is well suited for the former task (~80% accuracy), while the latter scenario still require deeper data analysis and exploration. In any case, the results obtained demonstrate that the presented preliminary research is highly promising, as the achieved results show a level of accuracy comparable to that obtained through the current human-based procedure actually adopted in concrete casting operations.

Keywords: Concrete mix design · Machine learning · Compressive strength · Cement reduction · Green concrete · Multi-layer perceptron.

1 Introduction

The European Green Deal pushes the international community to make a real commitment to decarbonisation by setting ambitious environmental targets: 55% reduction of CO_2 emissions by 2030, compared to 1990 levels, and carbon neutrality by 2050 [1]. The building sector is responsible for a significant fraction of overall energy consumption and pollution worldwide, and concrete is one of the most energy-intensive and polluting building material. In specific, the cement industry, the main component of concrete mix design, accounts for 8% to 10% of global CO_2 emissions [2,3], making it evident that the concrete industry plays a crucial role in the decarbonization process that our society is undergoing on multiple fronts, as shown in Fig. 1.

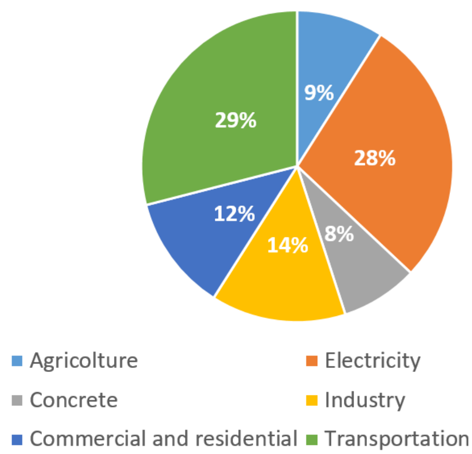


Fig. 1. Relevance of concrete in modern society

At the same time, concrete structures seem to be suitable for climate resilient construction due to their versatility and durability [4,5]. In addition to its well-known strength and resilience, concrete is a fundamental construction element because it is cost-effective and easy to produce. Worldwide, 30 billion tons of concrete are used each year, and the trend is expected to grow in the next few years. On a per capita basis, this is 40 times more than 40 years ago, and the demand for concrete is growing faster than for steel and timber [6]. Concrete is a construction material composed of aggregates, a binder, and water. Aggregates consist of sand, gravel, or crushed stone, while the binder is typically made of Portland cement mixed with water. To match specific requirements, concrete may incorporate supplementary cementing materials (SCMs) like fly ash or slag cement, as well as chemical admixtures

[7,8,9]. In literature - as well as in common practice - several methods are considered for evaluating concrete mixtures typically involving a trial-and-error approach, where proportions, processing, and characterization are iteratively adjusted until desired properties are achieved [10]. While this approach has shown some success, it requires significant investments of time. For instance, optimizing concrete strength involves adjusting various ratios such as water/cement, total aggregate/cement, and coarse aggregate/total aggregate. Applying this iterative refinement method becomes challenging when studying concrete mixtures with multifactorial compositional parameters. The exponential increase in required specimens and experiments limits practical application. Consequently, concrete science requires lengthy validation and development cycles from laboratory trials to real-world implementations. Therefore, expediting knowledge acquisition and materials design in concrete science is crucial. Such methods can be adopted to optimize the content of the different components. For example, known that cement is the most problematic in terms of CO_2 emissions, the optimization of its quantity assumes a fundamental role in the context of the global initiative to reduce greenhouse gases, where even a slight reduction can have a significant positive impact [11]. Actually, the production of cement involves a energy intensive process known as calcination, in which limestone (calcium carbonate) is heated to produce lime (calcium oxide), releasing carbon dioxide as a byproduct. Additionally, the chemical reaction of cement hydration, which occurs when water is added to cement, also contributes to CO_2 emissions. This is referred to as the indirect emissions associated with the production of cement. Therefore, it becomes essential to have a tool that enables a more precise determination of the properties of the final concrete product based on its initial mix design. By gaining a higher level of confidence in the properties of concrete considering its basic components, optimal solutions can be sought to minimize the cement content without compromising structural safety. Reducing uncertainties in the mix design process allows for a more environmentally friendly concrete mix with a reduced carbon footprint. In this paper, we present an innovative approach for determining the mechanical properties of concrete using deep learning methods [12,13,14,15]. Our study involves training and testing various neural networks models on a real-world database of mix designs. The objective is to achieve the higher accuracy in the estimation of two key properties of concrete: compressive strength, when hardened, and the consistency class, while still fresh.

Compressive strength is a critical parameter that ensures the safety and integrity of concrete. It is the most important parameter for structural design and verification. On the other hand, consistency class express the workability of the concrete mix during the casting process. Achieving the desired consistency is crucial for producing a homogeneous and well-performing final product [16]

2 Methodology

In this paper, an application of artificial neural networks for determining the physical and mechanical properties of concrete, based on the mix design, is presented. Specifically, different neural models were trained and tested on a real dataset consisting of approximately 1100 labeled mixture data.

2.1 Dataset description

The dataset, collected for the first time for this research, contains various parameters for each mix design, including:

- the type of cement (type II or type III);
- the quantity of cement (kilograms);
- the 28-day strength of the cement (cement class, 32.5 or 42.5);
- the amount of water added to the mixture (litres);
- the maximum diameter of aggregates (millimeters);
- the quantity of additives.

Additionally, for each mixture, the consistency class and the 28-day compressive strength of the concrete after casting are measured. These measurements serve as the target variables or labels to be predicted. The neural network models are trained using this dataset, with the input features being the known parameters of the mix design with the aim to predict the consistency class and the compressive strength of the concrete.

2.2 Consistency class

The first parameter to be determined is the concrete consistency class. Concrete is commonly classified into different consistency classes based on the results of the slump test.

The slump test is a widely used procedure to measure the workability or consistency of fresh concrete. It involves filling a slump cone, which is a frustum-shaped metal mold, with freshly mixed concrete. The cone is then carefully lifted, allowing the concrete to flow and settle. After removing the cone, the height difference between the original height of the cone and the settled concrete is measured, indicating the slump or settlement of the concrete. The problem of determining the consistency class can be approached as a classification problem, where the concrete mixture is assigned a specific class based on the measurement of slump.

2.3 Compressive strength

The second parameter to be predicted is the compressive strength of the concrete, which is measured after 28 days of casting. This parameter is of utmost importance as it directly influences the final strength and durability of the structure, making it a key factor in structural design and verification processes. Accurately estimating the compressive strength is crucial to ensure the structural integrity of the project and avoid potential risks.

The compressive strength, denoted as R_c, is determined through a compression test on cubic concrete samples with a side length of 15 cm. However, it is important to note that test results can exhibit variability, even within the same concrete batch. To account for this, statistical analysis is conducted to establish a distribution curve representing the concrete compressive strength. From this analysis, the characteristic compressive strength, denoted as R_{ck}, is defined as the 95th percentile of the strength normal distribution [17]. Based on the characteristic compressive strength, concrete can be assigned to specific strength classes, as outlined in Table 1. The determination of characteristic strength can be approached in two ways. Firstly, it can be treated as a regression problem, where the R_{ck} of concrete is calculated based on the mix design data. Alternatively, it can be framed as a classification problem, assigning concrete a strength class based on the mix design data.

Table 1. Compressive strength classes for concrete.

Strength class	R_{ck} [MPa]
C16/20	20
C20/25	25
C25/30	30
C30/37	37
C35/45	45
C40/50	50
C45/55	55
C50/60	60
C55/67	67
C60/75	75

In this work, the effectiveness of artificial neural networks was tested using both approaches to determine the method that yielded the highest accuracy [18]. Through training and evaluating various neural network models on the dataset, the study aimed to identify the most reliable and accurate approach for predicting the characteristic compressive strength of concrete. By comparing the results obtained from the regression and classification approaches, valuable insights were gained regarding their performance and suitability for practical applications.

3 Results and discussion

Several machine learning models for predicting the consistency class and compressive strength of concrete were trained and tested. All models were fed with the same input training set, normalized with z-score [19], described in Sec. 2. Three different target scenarios were investigated: SLUMP consistency classification (see Sec. 2.2); 28-days compressive strength regression; Rck classification (see Table 1).

3.1 Consistency class experiment

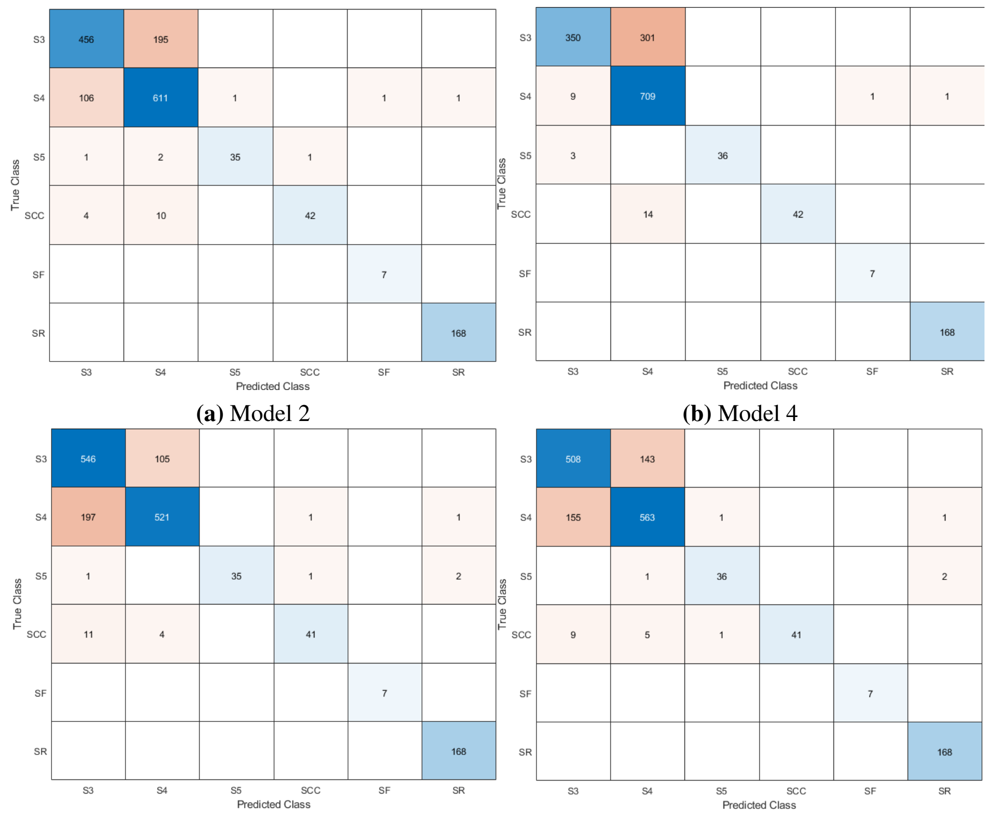
The first set of experiments dealt with classifying the input sequence into the appropriate SLUMP group. At this purpose, multiple multi-layer perceptrons [20,21] were trained, varying the amount of hidden layers (from 1 to 3), the amount of neurons per each layer, and their activation function. In all the experiments, softmax was used as output function to provide classification rankings. Table 2 reports the accuracy performance of the most significative ones. The best accuracies are slightly above 80%, meaning the proposed architectures are able to understand the phenomenon at hand. More in detail, Fig. 2 shows the confusion matrices [22] of the four most promising models on the whole dataset, due to the relatively low number of available data points. It can be seen that all the four models perfectly learns the SF and SR classes, and almost perfectly the S5 one (3-4 misclassified samples). The amount of false negatives for the SCC class is relatively small. On the contrary, S3 and S4 classes (the most numerous ones) are harder to be explained with the latter well mapped only by Model 4 at the expense of S3 classification (301 false negatives, see Fig. 2b), and vice-versa for S3 and three other networks with a superior performance of Model 13 (see Fig. 2c). In this sense, it can be stated that increasing the network complexity does not imply a strong advantage in terms of accuracy performances.

Table 2. Example of models trained for the consistency class prediction.

Model name	First layer size	Second layer size	Third layer size	Activation	Accuracy
1	10			ReLU	76.8
2	**25**			**ReLU**	**80.4**
4	**50**			**ReLU**	**80.0**
5	100			ReLU	80.0
6	50			Tanh	80.0
7	50			Sigmoid	80.1
8	86	12		ReLU	77.3
12	50	15		ReLU	80.2
13	**50**	**25**	**10**	**ReLU**	**80.3**
15	100	50	10	ReLU	80.1
17	**25**	**50**	**10**	**ReLU**	**80.6**
20	50	50	10	ReLU	80.3

3.2 Compressive strength experiments

In the second set of experiments, the input features were mapped to a single numerical value of the compressive strength measured in the laboratory facility after 28 days. This is obviously a much more complex scenario than before due also to the limited amount of



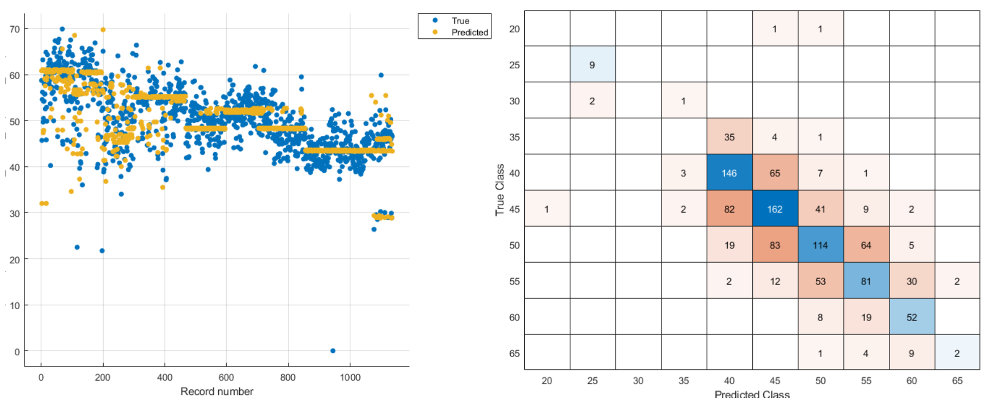
(a) Model 2 **(b)** Model 4

(c) Model 13 **(d)** Model 17

Fig. 2. Results for the consistency class classification of concrete mixtures using ANN.

data and the uncertainty they embed. All the trained models did not reach any satisfactory performance in regression. Fig. 3a yields an example of the regression result. As it can be easily seen, the network tends to cluster data along median values. To tackle this behavior, PCA preprocessing and normalization were attempted [23,24,25]; unfortunately, they did not resulted in any meaningful improvement.

Rck compressive strength classification Since the direct use of compressive strength value did not achieved satisfactory results, we decided to tackle the compressive strength scenario using the Rck taxonomy shown in Table 1. In this sense, the regression problem was turned into 10-class task, which we expected to be simpler with regard to the amount of samples in the dataset. To this purpose, different multilayer perceptrons were trained, with softmax as output function. The best performing one, whose confusion matrix is shown in Fig. 3b, has two hidden layer made of 10 neurons each and employs ReLu as activation function. The overall accuracy, considering all the values reported in the figure is nearby 50%. It must be noted that classes 20 and 30 are very poorly represented in the dataset (2 and 3 samples, respectively); therefore, they could be discarded from the overall accuracy computation. On the contrary, the performance on class 65 are not satisfactory at all. Finally, it can be stated that all values at the right of the blue squares (i.e. the main diagonal) are a conservative classification of the network with regards to the input data; in this sense, the proposed architecture mimics the human behaviour. Further researches will deepen this aspect to assess if these misclassifications are due to a sub-optimal architecture or to noisy/wrong input values of the mix design components; for example, the real amount of water in the mixture can increase/decrease depending on weather conditions, e.g. rainy/sunny days.



(a) Regression approach **(b)** Classification approach

Fig. 3. Results for the concrete compressive strength prediction using ANN.

4 Conclusion

Concrete is the world most widely used construction material due to its versatility, durability and economy but it accounts for 7-8% of global CO2 pollution. To minimize cement usage and reduce its environmental impact, it is essential to mitigate the uncertainties linking the initial mix design to the physical and mechanical properties of the final concrete.

This study demonstrated the potential of machine learning techniques in predicting the properties of concrete based on mixture data. The results indicate that the models developed in this study were able to predict the consistency class and the compressive strength of concrete using the mix design as input parameters. In the first scenario, the best performing neural architectures reached ~80% accuracy, while the latter case need further investigation, even though it already behaves as human-based approach. It must be noted that data are highly experimental and, therefore, they are affected from noise, e.g. the amount of water remaing uncertain due to external factors, such as weather conditions. Due to the limited amount of data (~1100), it was not possible to quantify their uncertainty.

Future works will deal with incorporating environmental data such as temperature and precipitation into the models to improve their accuracy. In this sense, experience suggests that considering such factors can be beneficial in optimizing concrete mix design. In parallel, much more experimental data wil be collected, which will allow to use more complex neural architectures, such as those based on 1D-CNNs [19]. However, to the best of our knowledge, this paper is one of the first ones to tackle concrete production using ML. In this sense, even if with preliminary data, this work can be considered as a frontier research one, and it paves the way to optimize concrete mix design process and, thus, potentially reduce CO2 emission worldwide.

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