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A Novel Artificial Neural Network to Predict Compressive Strength of Recycled Aggregate Concrete

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Abstract: Most regulations only allow the use of the coarse fraction of recycled concrete aggregate (RCA) for the manufacture of new concrete, although the heterogeneity of RCA makes it difficult to predict the compressive strength of concrete, which is an obstacle to the incorporation of RCA in concrete production. The compressive strength of recycled aggregate concrete is closely related to the dosage of its constituents. This article proposes a novel artificial neural network (ANN) model to predict the 28-day compressive strength of recycled aggregate concrete. The ANN used in this work has 11 neurons in the input layer: the mass of cement, fly ash, water, superplasticizer, fine natural aggregate, coarse natural or recycled aggregate, and their properties, such as: sand fineness modulus of sand, water absorption capacity, saturated surface dry density of the coarse aggregate mix and the maximum particle size. Two training methods were used for the ANN combining 15 and 20 hidden layers: Levenberg–Marquardt (LM) and Bayesian Regularization (BR). A database with 177 mixes selected from 15 studies incorporating RCA were selected, with the aim of having an underlying set of data heterogeneous enough to demonstrate the efficiency of the proposed approach, even when data are heterogeneous and noisy, which is the main finding of this work.

Keywords: construction and demolition waste; recycled concrete aggregate; compressive strength; artificial neural networks

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1. Introduction

Concrete is the second-most consumed material globally (after water). Every year more than 10 billion tons of concrete are used, and its production will increase between 12–23% until 2050 [1]. The production of one cubic meter of concrete emits between 0.2–0.4 tons of CO_2 [2] which represents 8% of global CO_2 emissions [3]. Furthermore, concrete is made up of aggregates (80% by weight), extracted mostly from alluvial deposits or quarries, which implies a high consumption of nonrenewable natural resources. The natural aggregates required to manufacture concrete could reach 60 billion tons in 2030 [4]. For all these reasons, concrete is considered an environmentally unfriendly material. At the end of their useful life, concrete structures are demolished, generating concrete waste with a high potential to be recycled [5].

One of the possible ways to reduce the carbon footprint and environmental impact of concrete is the replacement of natural aggregates (NA) with recycled concrete aggregates (RCA) [6]. In this way, it is possible to reduce the consumption of natural aggregates, avoid landfilling of concrete waste and promote the new paradigm of circular economy. RCAs are mainly composed of concrete and natural stone particles (>90% by weight).

Concrete particles are composed of natural aggregates covered with old mortar and cement paste. This layer is called attached mortar and represent between 20–30% of the RCA volume. The RCA properties are closely related to the type and quality of the attached mortar paste, which shows higher porosity, heterogeneity, and fragility in the interfacial transition zone [7,8] than natural aggregate. The mortar paste also shows tiny cracks that develop during the crushing process. Most of the studies relate the worst physical–mechanical and chemical properties of RCA with the presence of attached mortar paste [9]. RCA show a lower density, higher water absorption and less resistance to fragmentation than the NA [10]. From a chemical point of view, RCA show a higher number of sulfates and soluble salts than natural aggregates [11].

Most regulations only allow the use of the coarse RCA fraction for the manufacture of concrete [12]. The substitution of NA by RCA normally leads to a reduction in the mechanical properties of concrete (compressive and tensile strength, modulus of elasticity and abrasion resistance). Compressive strength at 28 days is the most representative property for evaluating the mechanical performance of concrete [5]. The compressive strength of concrete has been used in models to predict the modulus of elasticity and its evolution over time [13]. Additionally, the elastic modulus plays a significant role in the dynamics of Reinforced and Prestressed Concrete structures [14]. The increase in RCA content and water-to-cement ratio impairs the durability properties of concrete, such as water absorption by immersion and water absorption by capillarity, chloride penetration resistance, carbonation depth, frost resistance and acid resistance. From a rheological point of view, the shrinkage and creep increase [15,16]. The compressive strength is one of the parameters to be considered by the RILEM Technical Committee TC-242-MDC to predict creep, drying shrinkage and autogenous shrinkage of normal and high-strength concrete with multidecade applicability [17]. In order to produce a more durable recycled aggregate concrete it is suggested to use pozzolanic materials and CO_2 treatment prior to use in concrete [15].

The compressive strength of concretes made with recycled aggregates is closely related to the dosage of its constituents. The compressive strength of concrete depends mainly on the amount of cement, the water-to-cement ratio, the amount of sand and coarse aggregates, the use of additives and additions, the percentage of incorporation and the moisture conditions of the RCA [18]. The quality of the primitive concrete (high, medium or low strength) determines the water absorption capacity and the density of the RCA particles, which affects the compressive strength of the new concrete [19].

In this sense, most studies on the use of RCA in the manufacture of concrete show that the incorporation of the coarse fraction of RCA reduces the compressive strength values [20], although in some cases the values of the reference concrete are maintained [21]. Silva et al. [20] found that the incorporation of 100% coarse RCA reduces compressive strength by approximately 50%. Limbachiya et al. [22] found no differences if the percentage of substitution of NA for RCA was less than 30%. In this context, several authors have demonstrated the usefulness of RCA to obtain concretes good enough for construction purposes, but the heterogeneity of the materials used, and the diversity of the variables considered to estimate the compressive strength make it difficult to create a general way to estimate a priori the compressive strength of the resulting concrete, which complicates the generalization of the use of this type of concrete. So, it is necessary to explore the possibility to obtain good estimates of compressive strength without having to make individual tests for each one of the possible combinations, type of constituent and range of the physical properties of the materials used. In this way, Artificial Intelligence (AI) methods have been shown to be useful in this and other fields.

AI methods are useful to predict concrete parameters and they have been widely used in the literature. Recently, Artificial Neural Networks (ANN) have been used for estimating compressive strength of concrete [23,24] as well as other properties, since it is a powerful method for dealing with multivariable problems and generating easy-to-use models, even when the number of inputs is large. Artificial intelligence methods have been shown to be more accurate than multiple regression models (MLR) in predicting the compressive strength of concrete. For example, Patil et al. [25] have recently proposed an MLR to predict the 28-day compressive strength, taking into account the quantity of cement, natural fine aggregates, coarse recycled concrete aggregates, water, water-to-cement ratio, and the following aggregate properties: water absorption, specific gravity, aggregate impact value and aggregate abrasion value, finding R^2 values less than 0.55 in the training phase and less than 0.75 in the test phase, which highlights the invalidity of the MLR method to predict the mechanical properties of concretes. These same authors also proposed an ANN model with a better accuracy than the MLR model. The R^2 value of the ANN models was more than 0.8 in the training phase and more than 0.9 in the test phase, which shows that the ANN is a good alternative to predict the mechanical properties of RCA concrete.

Özcan et al. [26] compared the accuracy of obtaining the compressive strength of silica-fume concrete with Artificial Neural Networks (ANN) and Fuzzy Logic (FL). They used 48 different samples with four water-to-cement ratios, three cement dosages and three partial silica-fume replacement ratios, obtaining better results with ANN than with FL. Nevertheless, they concluded that ANN and FL can be alternative methods to predict compressive strength, since the number of samples as well as the number of input parameters used were small. In a similar way, Nazari and Riahi [27] compared ANN and Genetic Programming (GEP) for predicting split tensile strength and percentage of water absorption of concretes containing TiO_2 nanoparticles. They used 144 samples with 16 mixture proportions and cement content, nanoparticle content, aggregate type, water content, amount of superplasticizer, type of curing medium and age of curing were used as input variables. They obtained better results with ANN, but those obtained with GEP were reasonably accurate too, while this a simpler method. In a similar way, Nazari [28] modeled, by means of gene expression programming, the compressive strength of geopolymers produced by Portland cement as an aluminosilicate source. The main factors considered were NaOH concentration, water-glass-to-NaOH-weight ratio, alkali-activator-to-cement-weight ratio, oven curing temperature, oven curing time, and water curing regime, with each one of them at four levels. They obtained good results. Castelli et al. [29] used genetic programming with geometric, semantic, genetic operators to predict compressive strength of high-performance concrete using quantities of cement, fly ashes, blast furnace slag, water, superplasticizer, coarse aggregate, fine aggregate, and age of testing as input variables, outperforming the results previously obtained with standard genetic programing.

González-Taboada et al. [30] predicted compressive strength, modulus of elasticity, and splitting tensile strength of recycled concrete considering the recycled percentage, the quality of the recycled aggregates, and the production method. They analyzed 1831 samples obtained from 81 studies by means of multivariable regression and genetic programming, obtaining good enough results in comparison with those previously identified. Finally, Gholampour et al. [31] used gene expression programming for predicting mechanical properties of recycled aggregate concrete. As well as the above-mentioned authors, many samples were extracted from the literature. They proposed expressions for predicting compressive strength, elastic modulus, flexural strength, and splitting tensile strength, obtaining results comparable with the previously known models.

Recently, ANN have been used for estimating compressive strength of concrete [23,24] as well as other properties, since it is a powerful method for dealing with multivariable problems and giving easy-to-use models, even when the number of inputs is large. So, Moradi et al. [32] tried to predict the compressive strength of concrete containing metakaoline, extracting data from the literature in a total of 239 samples (in two sets of 105 and 134 samples, respectively). Results showed MSE of 0.002 and 0.0017, and their predicted data was within $\pm$20% of the sample data. In the same way, Kostić and Vasović [33] proposed a model estimating compressive strength of concrete by means of neural networks. They used 75 samples with various water-to-cement ratios, and their compressive strength was determined at different ages of 7, 20 and 32 days. They only used water-to-cement ratio, age, and number of freeze/thaw cycles as input variables, obtaining a coefficient of determination of $R^2 > 0.87$ and maintaining predicted data in $\pm$15% of sample data. Table 1 summarize the recent approaches to predict concrete's parameters by means of AI techniques. As Table 1 shows, there is a variety of papers searching for estimating different parameters of concretes based on their constituents (especially compressive strength), but there is no consensus about the number of subjacent input parameters to be considered, neither the number of previous tests to be carried out in order to obtain good predictions. Thus, there is still a question to be answered: whether there is a possibility of obtaining good predictions even when using a heterogeneous set of samples and a wide range of input values.

In this way, and according to the above-mentioned literature, several works study the usefulness of RCA as a good alternative to replace NA. Nevertheless, the variety of kind of materials used, and the wide range of their physical properties' values, make it difficult to obtain an accurate prediction of the compressive strength without the necessity of making individual and costly tests. This paper is focused on searching for an easy way to obtain a priori a prediction of the compressive strength of concretes made using RCA, even though the kind of constituents are heterogeneous and difficult to be classified, with the aim of providing a good working tool to concrete manufacturers. With this aim, several samples have been taken out from the literature, using different natural and recycled aggregates ratios from a variety of sources, to obtain a good estimation of 28-day compressive strength in the newly proposed model.

Table 1. Summary of AI approaches for estimating concrete parameters.

Authors	Year	Ref.	Technique	Input Parameters	Output Data	Number of Samples
Saridemir, M.	2009	[34]	ANN, Fuzzy Logic	Age, days Metakaolin, % Water–binder ratio, % Superplasticizer, % Binder–sand ratio, %	Compressive strength	179
Özcan, F. et al.	2009	[26]	ANN, Fuzzy Logic	Cement, kg/m^3 Silica fume, kg/m^3 Water, L/m^3 Plasticizer, L/m^3 Aggregate, kg/m^3) Age, days	Compressive strength	48
Nazari, A. et al.	2011	[27]	ANN, Genetic Programming	Cement, kg/m^3 Nano TiO_2, kg/m^3 Aggregate type Water, kg/m^3 Superplasticizer, kg/m^3 Curing medium Age of curing Number of tests	Split tensile strength and percentage of water absorption	144
Nazari, A.	2013	[28]	Genetic Programming	NaOH concentration Water glass–NaOH ratio Alkali activator–cement ratio Oven curing temperature Oven curing time Water curing regime	Compressive strength	32
Castelli, M. et al.	2013	[29]	Genetic Programming	Cement, kg/m^3 Fly ash, kg/m^3 Blast furnace slag, kg/m^3 Water, kg/m^3 Superplasticizer, kg/m^3 Coarse aggregate, kg/m^3 Fine aggregate, kg/m^3 Age of testing, days	Compressive strength	1028

Table 1. *Cont.*

Authors	Year	Ref.	Technique	Input Parameters	Output Data	Number of Samples
Duan Z et al.	2013	[24]	ANN	Water, kg/m^3 Cement, kg/m^3 Sand, kg/m^3 Natural aggregate, kg/m^3 Recycled aggregate, kg/m^3 Fineness modulus of sand Maximum size of coarse aggregate, mm Water–cement ratio Type of coarse aggregate Water absorption of coarse aggregate, % Saturated surface dry Specific gravity of coarse aggregate, g/cm^3 Replacement ratio by volume, % Conversion coefficient	Compressive strength	168
Gandomi, A. et al.	2014	[35]	Gene Expression Programming	Web width, mm Effective depth, mm Shear-span-to-depth ratio Concrete compressive strength, MPa Amount of longitudinal reinforcement, %	Shear strength	1942
Saridemir, M.	2014	[36]	Genetic Programming	Age of specimen Cement Sand Aggregate Superplasticizer Fly ash	Compressive strength	1976
Kostić, S. et al.	2015	[33]	ANN	Water–cement ratio Age Number of freeze/thaws	Compressive strength	75
González-Taboada, I. et al.	2016	[30]	Multivariable Regression and Genetic Programming	Recycled concrete compressive strength Recycled coarse aggregate percentage Recycled coarse aggregate water absorption	Compressive strength, Modulus of elasticity and Splitting tensile strength	1831
Chopra, P. et al.	2016	[37]	ANN and Genetic Programming	Water Cement Coarse aggregate Fine aggregate 28-day compressive strength	56-day compressive strength	76
Gandomi, A. et al.	2017	[38]	Gene Expression Programming	Web width, mm Effective depth, mm Shear-span-to-depth ratio Concrete compressive strength, MPa Amount of longitudinal reinforcement, % Amount of shear reinforcement, MPa	Shear strength	466

Table 1. *Cont.*

Authors	Year	Ref.	Technique	Input Parameters	Output Data	Number of Samples
Gholampour, A. et al.	2017	[31]	Gene Expression Programming	Recycled concrete aggregate replacement ratio, % Effective water-to-cement binder ratio	Compressive strength, Elastic modulus, Flexural strength, and Splitting tensile strength	650, 421, 346, 152
Patil et al.	2021	[25]	ANN Multiple linear regression	Cement, kg/m^3 Natural fine aggregate, kg/m^3 Recycled coarse aggregate, kg/m^3 Water, kg/m^3 Water–cement ratio Water absorption, % Specific gravity Aggregate impact value, % Aggregate abrasion value, %	Compressive strength Flexural strength Split tensile strength	185
Congro, M. et al.	2021	[39]	ANN	Fiber aspect ratio Matrix compressive strength Steel fiber volumetric fraction	Flexural strength	400
Lin, C.J. et al.	2021	[23]	ANN	Water, kg/m^3 Fine aggregate, kg/m^3 Coarse aggregate, kg/m^3 Blast Furnace Slag, kg/m^3 Fly ash, kg/m^3 Superplasticizer, kg/m^3	Compressive strength	482
Moradi, M.J. et al.	2021	[32]	ANN	Cement, kg/m^3 Metakaolin, kg/m^3 Water, kg/m^3 Coarse aggregate, kg/m^3 Fine aggregate, kg/m^3 Specific area of MK, m^2/kg SiO_2 content of MK, % Al_2O_3 content of MK, %	Compressive strength	239

2. Materials and Methods

A database with 177 mixes selected from 15 studies on the effect of incorporating RCA on the compressive strength of concrete were selected (Appendix A). The compressive strength of concrete is the strength of hardened concrete measured from cylindrical specimens (15 × 30 cm) or cubic specimens (10 × 10 cm) of concrete in a compression machine. The compressive strength of concrete is calculated by dividing the breaking load by the cross-sectional area that resists the load, using the megapascal (MPa) as the unit of measure. The following standards have been used in the referenced studies: ACTM C39 (Standard method for compressive strength of cylindrical concrete specimens), BS 1881-Part 116 (Testing concrete part 116: method for determination of compressive strength of concrete cubes) and EN 12390-3 (Testing hardened concrete—Part 3: compressive strength of test specimens).

In accordance with González-Taboada et al. [30] all RCA showed a water absorption capacity under 8.5%. The amount of components in a concrete mix, such as the mass of cement (C), fly ash (FA), water (W), superplasticizer (SP), fine natural aggregate (FNA), coarse natural or recycled aggregate (CNA, RCA) and their properties, such as: sand fineness modulus of sand (FM of FNA), water absorption capacity (WA), saturated surface dry density of the coarse aggregate mix (SSD), and maximum particle size of coarse aggregate

(TM), are the main factors selected as input parameters used to construct the ANN models. The 28-day compressive strength was the only output value considered in this study. All the results were converted into equivalent 15 × 30 cm cylindrical compressive strength [24]. Table 2. summarizes the properties of constituents used (detailed in Appendix A), their ranges, the amount of data in every one of them, mean and standard deviation. So, the set of data chosen for making the estimations is heterogeneous enough for the purposes of the proposed approach. The RILEM Technical Committee TC-242-MDC [17] also recommends considering all admixtures and reactive additives such as fly ash separately, to predict the creep, drying shrinkage and autogenous shrinkage of normal and high-strength concrete with multidecade applicability. This same technical committee highlighted the importance of the type of aggregate in the prediction of shrinkage and creep.

Table 2. Summarized values of the dataset used.

	C kg/m^3	FA kg/m^3	W kg/m^3	SP %	FNA kg/m^3	CAN kg/m^3	RCA kg/m^3	FM of FNA	WA %	SSD g/cm^3	TM mm
Range	180 ... 702	60 ... 305	130 ... 271	0.09 ... 5.07	536 ... 870	210 ... 1237	43 ... 1171	2.1 ... 2.64	0.71 ... 8.2	2.36 ... 2.66	10 ... 25
n	177	67	177	60	177	118	101	177	177	177	177
Mean	369.33	137.98	187.78	1.20	670.73	936.86	742.27	2.20	2.80	2.55	19.51
Std. Dev.	87.40	75.59	24.77	0.91	55.73	485.51	452.45	0.15	1.98	0.09	6.52

Artificial Neural Networks have been shown to be useful to obtain good predictions in nonlinear processes and have been successfully used in several fields as control, for pattern recognition, learning, medical diagnosis, and a wide range of engineering applications, among others [40], and they present a special effectiveness when data are incomplete and noisy. In general, an ANN has three layers: and input layer, where input parameters are represented; several hidden layers, where data are processed; and an output layer, where output data are presented. Each one of the elements in the layers is called a neuron. The layers are interconnected by means of weights that must be modified along a training process, to obtain better fitting between the previously observed data and those generated in the output layer.

The Artificial Neural Network used in this work has 11 neurons in the input layer and only 1 in the output layer, and four sets of trainings have been carried out combining 15 and 20 hidden layers (Figure 1.) with the training methods of Levenberg–Marquardt (LM) and Bayesian Regularization (BR). The first one, LM, is recommended for nonlinear optimization problems and it is supposed to display a better performance than the traditional Gauss–Newton Method. The second one, BR, gives a better generalization when data are difficult [41]. So, four training processes have been carried out to obtain the best possible fitting of the synaptic weights. For the training process of the ANN, data have been divided into three sets: a training set of 123 datapoints (70%), a validation set of 27 datapoints (15%), and a testing set of 27 datapoints (15%).

Finally, to delimit the errors existing between estimated and observed data, and consequently choose the best option among the four tested, we used the mean absolute error (*MAE*) Equation (1), complemented with the standard deviation, the mean absolute percentage error (*MAPE*) Equation (2), and the root mean square error (*RMSE*) Equation (3), as well as the correlation coefficient (R^2):

$$MAE = \frac{\sum_{i=1}^{n} |t_i - o_i|}{n} \tag{1}$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{t_i - o_i}{o_i} \right| \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (t_i - o_i)^2}{n}} \tag{3}$$

where t and o are the predicted and observed data, respectively, and n is the total amount of data.

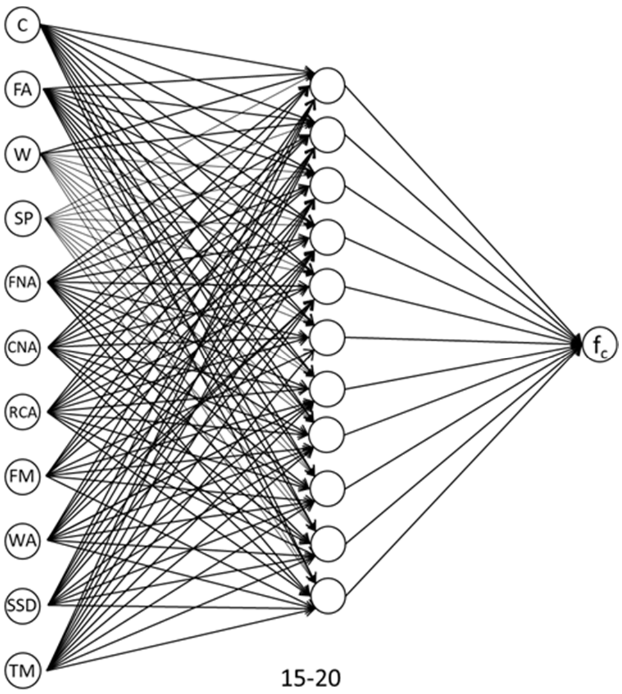

Figure 1. ANN architecture followed in the tests.

In the same way, the results obtained with the ANN have been compared with others from classical regression methods, such as Gaussian Process Regression (Matern 5/2), Support-Vector Machines (SVM), and Linear Regression.

Additionally, to determine the impact of the input parameters on the compressive strength values, new ANN have been carried out eliminating some of them. The following alternatives have been proposed: (i) unify the amount of cement (C) and fly ash (FA) in a single input parameter called the cementitious binder [42]; (ii) do not consider the superplasticizer input (SP), since the use of superplasticizer significantly reduces the amount of water (W) in the mix and both parameters could be related [43]; (iii) within the properties of the aggregates, the fineness modulus (FM) that indicates the average size of the sand particles; and iv) the maximum particle sizes ™ of the coarse fractures may be candidates not to be taken into account in the new ANN.

3. Results and Discussion

The results obtained with the ANN are good in all cases tested and have been summarized in Table 3 and in Figures 2 and 3.

Table 3. Summary of results obtained in ANN trainings.

Training Algorithm—Hidden Layers	MAE	Std. Dev.	MAPE	RMSE	R Training	R All
LM-15	1.79	3.26	4.46	3.27	0.99618	0.97133
LM-20	2.20	4.45	6.11	4.50	0.99734	0.95145
BR-15	**1.87**	**2.65**	**4.95**	**2.64**	**0.98895**	**0.98124**
BR-20	**1.58**	**2.35**	**4.12**	**2.34**	**0.98999**	**0.98526**

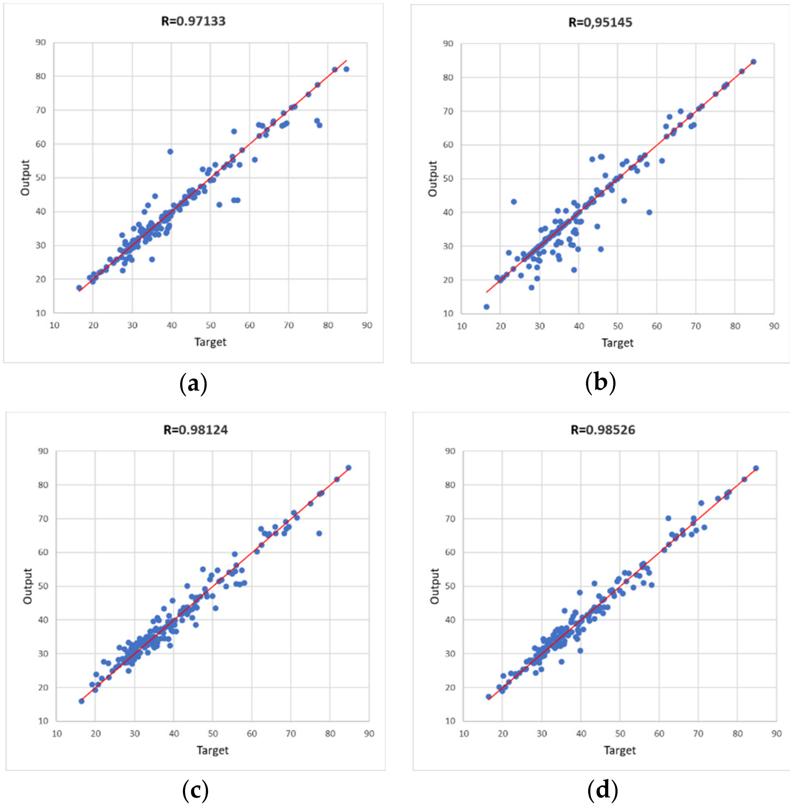

Figure 2. Correlations between target and output data for the four cases tested. (**a**): LM-15; (**b**): LM-20; (**c**) BR-15; (**d**): BR-20.

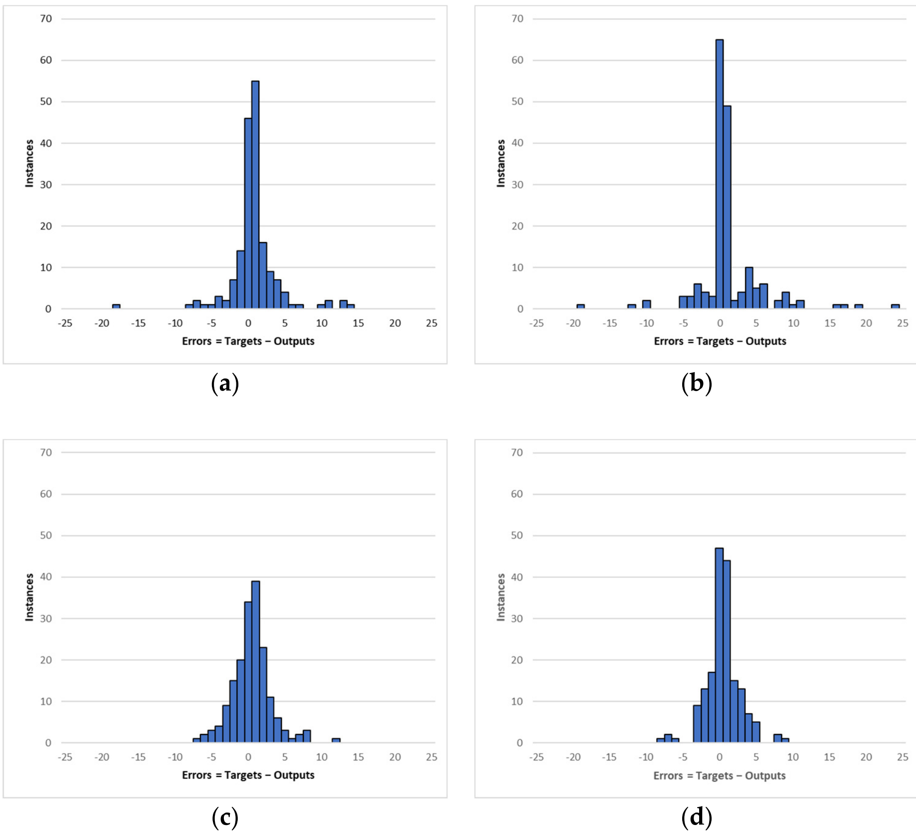

Figure 3. Distribution of errors for the training methods tested. (**a**): LM-15; (**b**): LM-20; (**c**) BR-15; (**d**): BR-20.

All the results obtained are good enough for estimating the compression strength of concrete with recycled aggregates. Furthermore, the BR training method has shown to be better than LM for obtaining predicted data perhaps due to the heterogeneity of the input data, which is justified by the different dosages and properties of the tested concretes. Especially, for the case of BR-20, 170 of 177 predicted compression resistances (96.05%) fall within a difference interval from −3 to +5 units away from target data, while in the case of BR-15, 176 outputs are between −7 and +8. In the case of LM-15, 170 outputs cover a range from −8 to +7 units of differences from targets, and in the case of LM-20, 160 outputs cover a range from −5 to +6. The test carried out with 20 hidden layers and Bayesian Regularization training method has been shown to be the best for all the metrics calculated.

Duan et al. [24] also developed an ANN model to predict the 28-day compressive strength of recycled aggregate concrete. These authors used 14 inputs: the mass of water, cement, sand, natural coarse aggregate, recycled coarse aggregate used in the mix designs, water-to-cement ratio of concrete, fineness modulus of sand, water absorption of the aggregates, saturated surface-dried (SSD) density, maximum size, and impurity content of recycled coarse aggregate, the replacement ratio of recycled coarse aggregate by volume, and the coefficient of different concrete specimens. All of these parameters were the same as those used in this study, except the impurity content of recycled coarse aggregate, the replacement ratio of recycled coarse aggregate by volume and the coefficient of different concrete specimens. The results obtained in the training set (146 sets) were: $R^2 = 0.998$; RMSE = 1.7958 and MAPE = 0.2622, while in the testing set (22 sets) they were $R^2 = 0.9955$; RMS = 3.6804 and MAPE = 1.6777. From an engineering point of view, the 14-input ANN model does not present significant differences with respect to the 11-input ANN models proposed in this study.

In order to compare the results obtained with the ANN, Gaussian Process Regression, Matern 5/2 (GPR); Support-Vector Machines (SVM); and Linear Regressions (LR) have been carried out on the same data using MATLAB. The results of each of these methods appear in Table 4. where the superiority of ANN over the other methods is clearly revealed.

Table 4. Results of regressions methods.

Method	MAE	RMSE	R All
GPR	2.793	3.5018	0.9487
SVM	2.8591	3.5099	0.9487
LR	3.1391	3.6435	0.9434

Once it is clear that ANN provides the best results for these kinds of data, there is still a question to be answered: whether it is possible to simplify the process of obtaining compressive strength predictions while eliminating some of the input data. For that purpose, four analyses have been carried out with the same ANN: (i) substituting C and FA by their sum; (ii) eliminating SP; (iii) eliminating FM of FNA; and (iv) eliminating TM. The results of each one of these new tests are shown in Table 5.

Table 5. Results of the simplified ANNs.

Method	MAE	Std. Dev.	MAPE	RMSE	R Training	R All
i	4.45	5.52	11.52	5.92	0.94589	0.91605
ii	2.04	2.75	5.32	2.74	0.98228	0.97994
iii	2.17	3.14	6.01	3.13	0.98347	0.97350
iv	**1.72**	**2.38**	**4.62**	**2.37**	**0.98756**	**0.98486**

In all the new cases tested, the results are worse than those obtained with the complete ANN. Only in the case (iv) of eliminating the maximum particle size of coarse aggregate (TM), are the results similar to those of the complete ANN. Regardless, the difference seems not to be enough to opt for this set of data, since it does not simplify the model substantially.

4. Conclusions

A novel ANN model has been presented in this paper for predicting compressive strength of concrete made with recycled concrete aggregates. The heterogeneity of RCA makes it difficult to predict the compressive strength of new concrete, which is an obstacle to the incorporation of this kind of aggregate in concrete production. Nevertheless, it has been proved that it is possible to obtain good predictions of the final 28-day compressive strength using the composition as input variables. In this case, 11 inputs variables have been used: the mass of cement (C), fly ash (FA), water (W), superplasticizer (SP), fine natural aggregate (FNA), coarse natural or recycled aggregate (CAN, RCA) and their properties, such as: sand fineness modulus of sand (FM of FNA), water absorption capacity (WA), saturated surface dry density of the coarse aggregate mix (SSD), maximum particle size of coarse aggregate (TM), and the resulting ANN, with 20 hidden layers, has shown to be accurate enough for a set of real data. Based on the results obtained, the best option is the Bayesian Regularization and 20 hidden layers. Additional tests attempting to analyze other regression methods, and simplified ANNs eliminating some inputs variables from the study, also gave good results, although the first-designed ANN was shown to obtain the best results. Furthermore, comparing with other studies aiming to obtain predictions of performance of concretes containing recycled aggregates [24,25], the results are similar or better in terms of accuracy, but the heterogeneity of data used in this study is an important factor, since results have been better or equivalent, even using a smaller amount of input data.

The proposed ANN model allows us to predict with enough accuracy the compressive strength value of a concrete from 11 input parameters, which will allow manufacturers to save time and laboratory testing when proposing new concrete dosages from recycled concrete aggregates of different sources and physical–mechanical properties.

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Appendix A

Table A1. Data base with 177 mixes selected from 15 studies on the effect of incorporating RCA.

N°	C	FA	W	SP	FNA	CNA	RCA	FM of FNA	WA	SSD	TM	Fc	Ref.
	kg	kg	kg	%	kg	kg	kg		%	g/cm^3	mm	MPa	
1	500	0	150	0.1	725	1087	0	2.11	1.1	2.62	10	77.2	[44]
2	400	100	150	0.16	707	1087	0	2.11	1.1	2.62	10	75.04	
3	637	0	150	2.89	711	936	0	2.16	1.1	2.62	10	77.92	[45]
4	475	158	150	2.89	681	924	0	2.16	1.1	2.62	10	84.72	
5	347	283	148	3.76	639	920	0	2.16	1.1	2.62	10	71.52	
6	702	0	135	5	641	949	0	2.16	1.1	2.62	10	77.44	
7	512	173	133	5.07	620	932	0	2.16	1.1	2.62	10	81.84	
8	372	305	130	4.99	608	927	0	2.16	1.1	2.62	10	70.8	
9	390	0	195	0	768	917	0	2.11	1.1	2.62	20	28.64	[46]
10	312	78	195	0	615	1143	0	2.11	1.1	2.62	20	31.44	
11	500	0	150	0.5	758	927	0	2.11	1.1	2.62	20	68.72	[47]
12	400	100	150	0.8	618	1147	0	2.11	1.1	2.62	20	66.16	
13	350	150	150	0.7	615	1143	0	2.11	1.1	2.62	20	64.16	
14	300	200	150	0.7	613	1139	0	2.11	1.1	2.62	20	61.36	
15	390	0	195	0	768	917	0	2.11	1.1	2.62	20	28.64	
16	273	117	195	0	626	1133	0	2.11	1.1	2.62	20	31.44	
17	234	156	195	0	625	1129	0	2.11	1.1	2.62	20	29.52	
18	350	115	175	1.6	785	735	0	2.64	0.85	2.63	20	38.8	[48]
19	270	145	160	2.23	870	750	0	2.64	0.85	2.63	20	51.6	
20	500	0	150	1.5	724	1086	0	2.16	1.1	2.62	10	69.44	[49]
21	425	75	150	1.5	700	1086	0	2.16	1.1	2.62	10	68.8	
22	375	125	150	1.85	683	1086	0	2.16	1.1	2.62	10	68.32	
23	275	225	150	2.1	650	1086	0	2.16	1.1	2.62	10	57.44	
24	225	275	150	2.6	634	1086	0	2.16	1.1	2.62	10	45.92	
25	400	0	160	1	710	1157	0	2.16	1.1	2.62	20	48.56	
26	340	60	160	1.1	690	1157	0	2.16	1.1	2.62	20	44.8	
27	300	100	160	1.2	660	1157	0	2.16	1.1	2.62	20	39.44	
28	220	180	160	1.3	634	1157	0	2.16	1.1	2.62	20	35.12	
29	180	220	160	1.6	621	1157	0	2.16	1.1	2.62	20	29.84	
30	410	0	205	0	609	1132	0	2.16	1.1	2.62	20	40.64	
31	348.5	61.5	205	0	589	1132	0	2.16	1.1	2.62	20	39.12	
32	307.5	102.5	205	0	576	1132	0	2.16	1.1	2.62	20	33.36	
33	225.5	184.5	205	0	549	1132	0	2.16	1.1	2.62	20	28.48	
34	184.5	225.5	205	0	536	1132	0	2.16	1.1	2.62	20	19.2	
35	500	0	150	1.5	724	1086	0	2.16	1.1	2.62	10	66	[49]
36	425	75	150	1.5	700	1086	0	2.16	1.1	2.62	10	62.32	
37	375	125	150	1.85	683	1086	0	2.16	1.1	2.62	10	63.28	
38	275	225	150	2.1	650	1086	0	2.16	1.1	2.62	10	51.2	
39	225	275	150	2.6	634	1086	0	2.16	1.1	2.62	10	45.68	
40	400	0	160	1	710	1157	0	2.16	1.1	2.62	20	44.64	
41	340	60	160	1.1	690	1157	0	2.16	1.1	2.62	20	35.84	
42	300	100	160	1.2	660	1157	0	2.16	1.1	2.62	20	35.28	
43	220	180	160	1.3	634	1157	0	2.16	1.1	2.62	20	26.16	
44	180	220	160	1.6	621	1157	0	2.16	1.1	2.62	20	25.92	
45	410	0	205	0	609	1132	0	2.16	1.1	2.62	20	34.08	
46	348.5	61.5	205	0	589	1132	0	2.16	1.1	2.62	20	30.48	
47	307.5	102.5	205	0	576	1132	0	2.16	1.1	2.62	20	28.16	
48	225.5	184.5	205	0	549	1132	0	2.16	1.1	2.62	20	24.32	
49	184.5	225.5	205	0	536	1132	0	2.16	1.1	2.62	20	20.72	

Table A1. *Cont.*

N°	C	FA	W	SP	FNA	CNA	RCA	FM of FNA	WA	SSD	TM	Fc	Ref.
	kg	kg	kg	%	kg	kg	kg		%	g/cm^3	mm	MPa	
50	410	0	225	0	642	1048	0	2.11	1.1	2.62	20	38.88	[50]
51	410	0	225	0	642	840	204	2.11	1.62	2.61	20	36.24	
52	410	0	225	0	642	524	506	2.11	2.41	2.58	20	34	
53	410	0	225	0	642	210	814	2.11	3.22	2.56	20	31.36	
54	410	0	225	0	642	0	1017	2.11	3.77	2.54	20	29.68	
55	307.5	102.5	225	0	628	1048	0	2.11	1.1	2.62	20	37.68	
56	307.5	102.5	225	0	628	840	204	2.11	1.62	2.61	20	35.04	
57	307.5	102.5	225	0	628	524	506	2.11	2.41	2.58	20	34.24	
58	307.5	102.5	225	0	628	210	814	2.11	3.22	2.56	20	31.12	
59	307.5	102.5	225	0	628	0	1017	2.11	3.77	2.54	20	29.36	
60	410	0	225	0	642	0	1017	2.11	3.77	2.53	20	30.48	[51]
61	307.5	102.5	225	0	611	1048	0	2.11	1.11	2.62	20	34.88	
62	307.5	102.5	225	0	611	840	204	2.11	1.64	2.6	20	34.24	
63	307.5	102.5	225	0	611	524	506	2.11	2.44	2.58	20	33.36	
64	307.5	102.5	225	0	611	0	1017	2.11	3.77	2.53	20	29.44	
65	266.5	143.5	225	0	598	1048	0	2.11	1.11	2.62	20	32.56	
66	267.5	143.6	225	0	598	840	204	2.11	1.64	2.6	20	32.8	
67	268.5	143.7	225	0	598	524	506	2.11	2.44	2.58	20	29.68	
68	269.5	143.8	225	0	598	0	1017	2.11	3.77	2.53	20	20.16	
69	400	0	180	0	708	1108	0	2.11	1.11	2.62	20	53.44	
70	400	0	180	0	708	886	215	2.11	1.64	2.6	20	49.92	
71	400	0	180	0	708	554	538	2.11	2.44	2.58	20	45.44	
72	400	0	180	0	708	0	1075	2.11	3.77	2.53	20	41.68	
73	300	100	180	0	688	1108	0	2.11	1.11	2.62	20	43.52	
74	300	100	180	0	688	886	215	2.11	1.64	2.6	20	39.76	
75	300	100	180	0	688	554	538	2.11	2.44	2.58	20	35.44	
76	300	100	180	0	688	0	1075	2.11	3.77	2.53	20	31.6	
77	260	140	180	0	688	1108	0	2.11	1.11	2.62	20	36.72	
78	260	140	180	0	688	886	215	2.11	1.64	2.6	20	34.88	
79	260	140	180	0	688	554	538	2.11	2.44	2.58	20	32.32	
80	260	140	180	0	688	0	1075	2.11	3.77	2.53	20	30.64	
81	390	0	195	0	678	1107	0	2.11	1.12	2.62	20	46	[11]
82	390	0	195	0	678	527	539	2.11	2.56	2.57	20	42.24	
83	390	0	195	0	678	0	1078	2.11	4.01	2.52	20	39.2	
84	253.5	136.5	195	0	640	1107	0	2.11	1.12	2.62	20	34	
85	253.5	136.5	195	0	640	527	539	2.11	2.56	2.57	20	34.8	
86	253.5	136.5	195	0	640	0	1078	2.11	4.01	2.52	20	29.6	
87	380	0	190	0	687	1120	0	2.11	0.74	2.64	20	44.8	[52]
88	380	0	190	0	687	0	1025	2.11	6.74	2.4	20	39.84	
89	380	0	190	0	687	0	1039	2.11	3.03	2.44	20	40.32	
90	380	0	190	0	687	0	1043	2.11	1.87	2.44	20	42.08	
91	355	0	195	0	690	1127	0	2.11	1.11	2.62	20	35.04	
92	355	0	195	0	690	902	205	2.11	1.6	2.6	20	33.52	
93	355	0	195	0	690	564	543	2.11	2.41	2.57	20	30.56	
94	355	0	195	0	690	0	1085	2.11	3.76	2.52	20	29.2	
95	355	0	195	0	690	902	193	2.11	1.97	2.58	20	32.96	
96	355	0	195	0	690	564	520	2.11	3.44	2.52	20	29.12	
97	355	0	195	0	690	0	1038	2.11	5.96	2.42	20	27.44	
98	355	0	195	0	690	902	199	2.11	2.04	2.6	20	33.28	
99	355	0	195	0	690	564	534	2.11	3.6	2.55	20	30.24	
100	355	0	195	0	690	0	1068	2.11	6.23	2.48	20	28.48	
101	353	0	209	0	666	1093	0	2.11	1.24	2.62	20	36.8	[8]
102	353	0	206	0	661	864	216	2.11	2.34	2.57	20	34.4	
103	353	0	207	0	649	531	531	2.11	3.98	2.49	20	30.48	
104	353	0	209	0	625	0	1026	2.11	6.71	2.36	20	31.28	

Table A1. *Cont.*

N°	C	FA	W	SP	FNA	CNA	RCA	FM of FNA	WA	SSD	TM	Fc	Ref.
	kg	kg	kg	%	kg	kg	kg		%	g/cm^3	mm	MPa	
105	353	0	214	0	667	1086	0	2.11	1.24	2.62	20	38.64	[8]
106	353	0	221	0	667	1080	0	2.11	1.24	2.62	20	32.16	
107	353	0	217	0	660	861	209	2.11	2.31	2.57	20	35.92	
108	353	0	230	0	661	853	202	2.11	2.29	2.57	20	34.56	
109	353	0	229	0	647	527	513	2.11	3.94	2.49	20	35.76	
110	353	0	247	0	647	524	496	2.11	3.9	2.49	20	31.76	
111	353	0	241	0	625	0	993	2.11	6.71	2.36	20	37.44	
112	353	0	271	0	625	0	959	2.11	6.7	2.36	20	34.64	
113	379	0	190	0	623	1237	0	2.1	1.24	2.62	20	33.2	[7]
114	379	0	190	0	590	0	1171	2.1	8.2	2.41	20	26.08	
115	379	0	190	0	590	0	1171	2.1	6.61	2.39	20	30.96	
116	420	105	184	0.7	668	1002	0	2.11	1.1	2.62	20	56	[53]
117	420	105	184	0.7	668	0	916	2.11	6.49	2.4	20	39.68	
118	420	105	184	0.7	668	0	938	2.11	5.55	2.45	20	43.44	
119	420	105	184	0.7	668	0	922	2.11	5.81	2.41	20	50.72	
120	420	105	184	0.7	668	0	940	2.11	5.53	2.46	20	56	
121	420	105	184	0.7	668	0	923	2.11	6.59	2.41	20	58.16	
122	300	0	205	0	697	1143	0	2.19	1.01	2.6	20	27.6	[54]
123	300	0	205	0	697	0	1075	2.19	3.36	2.48	20	28	
124	300	0	205	0	697	0	1027	2.19	6.14	2.36	20	23.36	
125	300	0	205	0	697	0	1040	2.19	6.44	2.36	20	22.16	
126	350	0	180	0	706	1158	0	2.19	1.01	2.6	20	38.64	
127	350	0	180	0	706	0	1089	2.19	3.36	2.48	20	38.08	
128	350	0	180	0	706	0	1041	2.19	6.14	2.36	20	33.6	
129	350	0	180	0	706	0	1054	2.19	6.44	2.36	20	34.32	
130	425	0	185	0	696	1092	0	2.19	1.01	2.6	20	49.28	
131	425	0	185	0	696	0	1028	2.19	3.36	2.48	20	48	
132	425	0	185	0	696	0	982	2.19	6.14	2.36	20	42.96	
133	425	0	185	0	696	0	994	2.19	6.44	2.36	20	42.56	
134	485	0	165	0	685	1094	0	2.19	1.01	2.6	20	64.4	
135	485	0	165	0	685	0	1030	2.19	3.36	2.48	20	62.56	
136	485	0	165	0	685	0	979	2.19	6.14	2.36	20	56.96	
137	485	0	165	0	685	0	982	2.19	6.44	2.36	20	52.32	
138	350	0	180	0	675	0	1089	2.19	6.14	2.36	20	39.36	
139	350	0	180	0	654	0	1041	2.19	6.44	2.36	20	34.88	
140	425	0	185	0	637	0	1028	2.19	6.14	2.36	20	48.32	
141	425	0	185	0	618	0	982	2.19	6.44	2.36	20	45.84	
142	440	0	155	0	666	1166	0	2.19	0.71	2.66	20	55.68	
143	440	0	155	0	666	0	1070	2.19	6.38	2.41	20	47.52	
144	440	0	155	0	666	0	1077	2.19	5.18	2.42	20	55.84	
145	440	0	155	0	666	0	1083	2.19	5.36	2.44	20	54.24	
146	440	0	155	0	666	0	1090	2.19	5.3	2.45	20	54.96	
147	440	0	155	0	666	0	1094	2.19	5.36	2.46	20	49.68	
148	380	0	190	0	710	1110	0	2.19	0.71	2.66	20	43.52	
149	380	0	190	0	710	1055	44	2.19	1.27	2.63	20	43.52	
150	380	0	190	0	710	999	88	2.19	1.85	2.61	20	43.92	
151	380	0	190	0	710	944	132	2.19	2.44	2.58	20	42	
152	380	0	190	0	710	1055	43	2.19	1.53	2.63	20	43.36	
153	380	0	190	0	710	999	86	2.19	2.38	2.61	20	41.84	
154	380	0	190	0	710	944	129	2.19	3.24	2.61	20	37.52	
155	370	0	185	0	732	1090	0	2.19	1.01	2.6	20	38.56	
156	370	0	185	0	732	545	463	2.19	2.31	2.55	20	40.24	
157	370	0	185	0	732	0	924	2.19	3.85	2.49	20	39.36	

Table A1. *Cont.*

N°	C	FA	W	SP	FNA	CNA	RCA	FM of FNA	WA	SSD	TM	Fc	Ref.
	kg	kg	kg	%	kg	kg	kg		%	g/cm^3	mm	MPa	
158	425	0	192	0.19	730	963	0	2.58	1.4	2.61	25	35.52	[55]
159	428	0	193	0.18	734	969	0	2.58	1.4	2.61	25	34.24	
160	429	0	193	0.22	736	729	230	2.58	2.24	2.58	25	30.16	
161	423	0	190	0.18	726	479	453	2.58	3.1	2.54	25	31.44	
162	427	0	192	0.28	733	242	687	2.58	3.99	2.51	25	28.24	
163	426	0	192	0.35	731	0	913	2.58	4.9	2.47	25	30.08	
164	431	0	195	0.1	741	489	457	2.58	3.33	2.53	25	28.08	
165	433	0	195	0.27	744	0	918	2.58	5.4	2.44	25	29.04	
166	427	0	192	0.19	734	484	451	2.58	3.28	2.52	25	26.88	
167	432	0	194	0.23	742	0	912	2.58	5.3	2.43	25	27.52	
168	430	0	193	0.2	737	0	917	2.58	4.7	2.46	25	25.28	
169	429	0	193	0.22	737	0	909	2.58	5.1	2.44	25	27.28	
170	316	0	194	0.11	803	953	0	2.58	1.4	2.61	25	23.44	
171	320	0	192	0.13	819	0	914	2.58	4.9	2.47	25	21.68	
172	322	0	193	0.09	823	0	908	2.58	5.4	2.44	25	19.92	
173	320	0	192	0.1	819	0	899	2.58	5.3	2.43	25	16.4	
174	645	0	194	0.36	563	973	0	2.58	1.4	2.61	25	46.8	
175	645	0	193	0.46	563	0	921	2.58	4.9	2.47	25	36.4	
176	642	0	192	0.51	561	0	905	2.58	5.4	2.44	25	45.68	
177	642	0	192	0.44	561	0	902	2.58	5.3	2.43	25	37.68	

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