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PREDICTING THE COMPRESSIVE STRENGTH OF ULTRA-LIGHTWEIGHT CONCRETE BY AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Ultra-lightweight concrete (ULWC) has potential applications for floating structures and architectural elements because of its dry density coming in at under 1000 kg/m^3. The objective was to develop an artificial neural network (ANN) to aid the ULWC designer according to his needs. Boundary conditions were set for each material and 13 constraints based on the water binder ratio, density, air content, binder and aggregate content. The ANN predicted the compressive strength with a comfortable margin of error, with the gap encountered being attributed to variability in workability. Precise constraints and boundary conditions are needed to ensure a lower variability in workability. The ANN, coupled with a genetic algorithm, can generate millions of mixes for a given compressive strength in a short amount of time. The designer is able to choose mixes according to additional needs, such as the carbon footprint, absolute density, polymer content, cost, etc.

Keywords: Ultra-Lightweight Concrete (ULWC), Concrete modelling, Artificial Neural Network (ANN), Genetic Algorithm (GA).

1. INTRODUCTION

Ultra-lightweight concrete (ULWC) has potential applications as floating structures and architectural elements. ULWC are fire resistant, insulating, and decorative. Lightweight concrete (LWC) has been available since the 1950s, and has been beneficial for high rise buildings (Xu et al., 2012). With a density below 1000 kg/m^3, ULWC pushes design challenges further, and allows the fabrication of advanced steel-concrete-steel composite structures (Sohel et al., 2012), boats and other floatable elements. Given the white color of ULWC, the material can easily be colored with stains and pigments. As well, ULWC features a low slump workability, which is required for the prefabrication of many architectural elements (Kosmatka et al., 2011).

Artificial neural networks (ANN) have traditionally been used to design high performance concrete (Baykasoğlu, Öztaş et Özbay, 2009; Öztaş et al., 2006), LWC (Alshihri, Azmy et El-Bisy, 2009) and no-slump concrete (Sobhani et al., 2010), but presently, no assistance is available in formulating ultra-lightweight concrete. The aim of this study is to determine whether the compressive strength of ULWC can be predicted using an ANN.

An artificial neural network (ANN) is a mathematical model that aims to represent the different aspects of biological neural networks. Over the past decade, ANNs have repeatedly been used successfully for machine learning in a vast range of fields. Results obtained by Yeh (2007) showed that for high-performance concrete, an ANN was more accurate than second-order regression in predicting a slump. The author also emphasized the fact that ANN models have become convenient and easy to use for such experiments. Öztaş et al. (2006) showed that an ANN is a strong tool for predicting the compressive strength and slump of high strength concrete by using a 187 mix-design database. Duan, Kou et Poon (2013) used an ANN to predict the compressive strength of a recycled aggregate concrete with a total of 14 input parameters. The results obtained on a 146-mix dataset suggested that the ANN had a good potential as a prediction tool for compressive strength. They also used the same metrics as were used by Öztaş et al. (2006). Özcan et al. (2009) showed that artificial neural networks and fuzzy logic are good alternatives for predicting the compressive strength of a 48-mix dataset of silica fume concrete. Similarly, the results of Sobhani et al. (2010) indicated that both the ANN and adaptive network-based fuzzy inference systems (ANFIS) are better than traditional regression models in predicting the 28-day compressive strength of no-slump concrete. The results of the work of Alshihri, Azmy et El-Bisy (2009) suggested that an ANN is an efficient tool for predicting the compressive strength of lightweight concrete using eight input parameters. Bilim et al. (2009) used an ANN model on a dataset of 45 ground granulated blast furnace slag concrete mixes with 6 input parameters, and the results showed that the ANN is a good alternative approach for predicting compressive strength. The results of Sarıdemir (2009) showed that for a database of 195 concrete mixes containing metakaolin and silica fume, ANN models have a strong potential to predict 1-, 3-, 7-, 28-, 56-, 90- and 180-day compressive strength. All these previous studies used the back-propagation network (BPN) architecture to construct the ANN models.

In this work, the back-propagation network architecture was used because of its simplicity and its ability to predict the compressive strength of different kinds of concretes, as has been shown in previous studies. More information regarding the BPN architecture and its construction can be found in Hecht-Nielsen (1989), as well as in the MATLAB neural network toolbox.

2. METHODOLOGY

The methodology is divided into two different sections, and is presented in chronological order. The development of the concrete mix database will be presented first, followed by an outline of the artificial neural network (ANN) procedure.

2.1 Concrete mix database

A total of 128 ULWC mixes were designed to create the database for the calibration of the ANN. The database was created by the Concrete Canoe Team at École de technologie supérieure (ÉTS) in Montreal, Canada. The ULWC used for the Concrete Canoe Team is different from standard lightweight concrete in many ways. Furthermore, to comply with the competition objectives, rules and regulations, different materials and constraints were carefully selected in developing the 128-mix database.

The team used ultra-lightweight aggregates (ULWA) to drop the density below that of water. Two post-consumer recycled expanded glass bead (REGB) (0.5 – 1.0 mm and 0.25 – 0.50 mm) sizes were used as ULWA because of their low density (190 – 530 kg/m^3). Glass microspheres (GM) made of extremely low density (120 kg/m^3) soda-lime borosilicate were used to lower the mix density, with their spherical size rendering the mix fluid, thus allowing better workability. The surface of the aggregates used was white in color, ensuring a white hardened concrete product.

Different latex solutions were used to achieve low slump workability. Two liquid latex solutions, namely, an acrylic based polymer emulsion (APE) and a high performance styrene-butadiene-rubber latex emulsion (SBRE), did improve the elasticity modulus and the mechanical properties. A polycarboxylate superplasticizer was also used for its latex compatibility, rheological properties, and to give the desired hand placement workability. For the ULWC mixture used in this study, there is no water added, and all the water present comes from the latex solutions.
Finally, to provide a clear white aesthetical finish, general use (GU) white Portland cement was used. A granulated blast furnace slag was also used for sustainability and to ensure compliance with ASCE competition rules and regulations.

The fabrication, curing and testing methods of the ULWC were based on ASTM C39 and C192 (ASTM, 2014a; 2014b) in order to ensure that the results were high repeatable and of high quality. To limit the amount of concrete produced, 5 cylinder specimens each measuring 50 mm in diameter and 100 mm in height were made for each mix.

To accommodate possible density segregation, a frequently observed problem when using LWA, three layers were used instead of two as stated in ASTM C192. Also, consolidation was carried out using 25 strokes of rod on each of the three layers, instead of vibrations. Using rods is also the closest way to consolidate the concrete to the concrete canoe fabrication and other usages of rodding in concrete forms (American Concrete Institute, 2005).

2.2 Artificial neural network (ANN)

The chosen ANN consists of an 8-neuron input layer, a 6-neuron hidden layer, and a single neuron output layer, and is represented in Figure 1. The neurons of the input layers represent the masses of the different materials added to the concrete mixture in kilograms, while the neuron in the output layer represents the 14-day compressive strength in MPa.

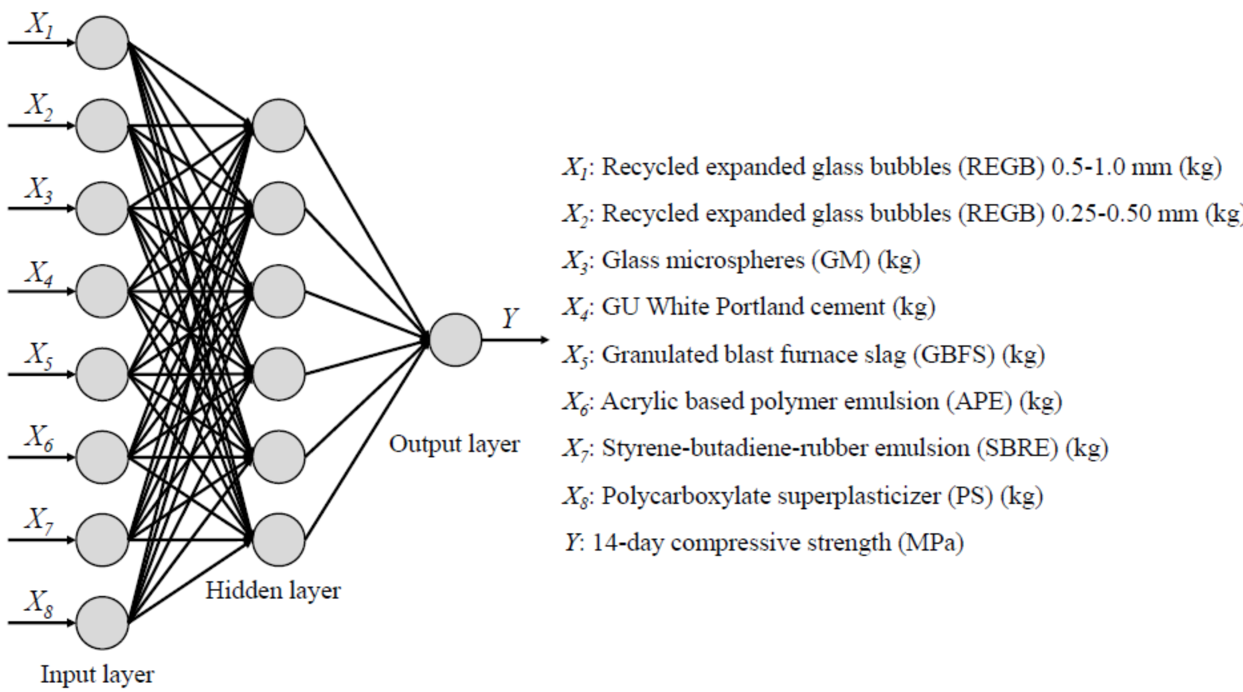

Figure 1: Artificial neural back-propagation network architecture used in this study

The MATLAB neural network toolbox was used to construct and calibrate the ANN. The 128-mix dataset was used during the calibration process, with 80% of the mixes (102 mixes) used for calibration, 10% (13 mixes) used for validation, and the remaining 10% (13 mixes) used for the testing of the artificial neural network.

Different metrics were used to evaluate the performance of the ANN, and a metric that had been used in previous studies was used as a comparison baseline. In those studies, the absolute fraction of variance was used to evaluate the performance of the ANN in predicting the compressive strength of different type of concretes: high-strength concrete (Öztaş et al., 2006), recycled aggregate concrete (Duan, Kou et Poon, 2013), and concrete containing metakaolin and silica fume (Sarıdemir, 2009). The metrics chosen were the Pearson's linear correlation coefficient (r), the normalized root-mean-square error (NRMSE), and the absolute fraction of variance (R^2). These equations were computed with equations 1 to 3, respectively. In these equations, t is the target value (lab value), o is the output value (ANN predicted value), n is the total number of mixes, $cov_{t,o}$ is the covariance between the target and output values, σ is the standard deviation, and j is the time step.

[1] $$r = \frac{\mathrm{cov}_{t,o}}{\sigma_t \sigma_0}$$

[2] $$NRMSE = \frac{\sqrt{\frac{1}{n}\Sigma_j\left(t_j - o_j\right)^2}}{\max\left(o_j\right) - \min\left(o_j\right)}$$

[3] $$R^2 = 1 - \left(\frac{\Sigma_j\left(t_j - o_j\right)^2}{\Sigma_j\left(o_j\right)^2}\right)$$

To generate mixes using the calibrated ANN, a genetic algorithm can be used to obtain a mix of the desired 14-day compressive strength. Using this methodology, a large number of mixes can be generated to evaluate different objectives other than the compressive strength, such as the carbon footprint, absolute density, polymer content or density. The maximal and minimal amount of each material, provided in Table 1, ensure some degree of consistency in the mechanical, rheological and architectural properties of the mixes. The constraints shown in Table 2 were based on minimal and maximal amounts of materials for one cubic meter of concrete in terms of cementitious materials, aggregates, latex and limitation of the water/binder (W/B) ratio. The minimal and maximal values and the exclusion rules showed in Table 1 and Table 2 were based on the experience of the mix designer and on particular usage requirements.

Table 1: Materials used in the ULWC and boundary conditions for the generation of mixes using the ANN

Parameter	Materials	Min. (kg/m^3)	Max. (kg/m^3)
X_1	Recycled expanded glass bubbles (REGB) 0.5-1.0 mm	30	150
X_2	Recycled expanded glass bubbles (REGB) 0.25-50 mm	10	150
X_3	Glass microspheres (GM)	20	50
X_4	GU White Portland cement	100	300
X_5	Granulated blast furnace slag (GBFS)	100	300
X_6	Acrylic based polymer emulsion (APE)	20	200
X_7	Styrene-butadiene-rubber emulsion (SBRE)	20	300
X_8	Polycarboxylate superplasticizer (PS)	4	50

Table 2: Constraints of the ULWC used in the generations of mixes using the ANN

Constraints	Excluding Rules (kg of material/m^3 of concrete)	Utility
1	$(X_6 + X_7) < 200$	Minimal workability of the mixture
2	$\Sigma X_n < 600$	Minimal density
3	$\Sigma X_n > 1000$	Maximal density
4	$X_1 + X_2 + X_3 > 250$	Maximal aggregate content
5	$X_1 + X_2 + X_3 < 100$	Minimal aggregate content
6	$X_4 + X_5 > 600$	Maximal binder content
7	$X_4 + X_5 < 200$	Minimal binder content
8	$X_4 / (X_4 + X_5) < 0.5$	Concrete canoe competition rules
9	$X_4 / (X_4 + X_5) > 0.3$	Concrete canoe competition rules
10	$\Sigma X_n/(\rho_n * 1000) - (X_1 * absX_1) / 1000 - (X_2*absX_2)/1000 < 0.925$	Maximal air content
11	$\Sigma X_n/(\rho_n * 1000) - (X_1 * absX_1) / 1000 - (X_2*absX_2)/1000 < 1.000$	Maximal absolute volume per cubic meter
12	$(X_6(1 - SF_6) + X_7(1 - SF_7) + X_8(1 - SF_8) - X_1 * AB_1 - X_2 * AB_2)/(X_4 + X_5) < 0.30$	Minimal W/B ratio
13	$(X_6(1 - SF_6) + X_7(1 - SF_7) + X_8(1 - SF_8) - X_1 * AB_1 - X_2 * AB_2)/(X_4 + X_5) > 0.55$	Maximal W/B ratio

SF = Solid fractions AB = Absorption

During the calibration of an artificial neural network, a testing dataset is used to validate its performance. Another testing dataset was used to test the limits of the prediction ability of the ANN. To that end, a set of mixes were generated without any recycled expanded glass beads for the 0.25-0.50 mm size range (No REGB 0.25 – 0.50 mm dataset). Since the artificial neural network was not calibrated on mixes without this material, the limits of the mathematical tool could be evaluated, and a determination could be made as to whether a good enough prediction was possible for such a case. To that end, the genetic algorithm was used to generate mixes of a desired 14-day compressive strength, and the boundaries and constraints were adapted to fit this new condition. A total of 11 mixes were generated, ranging from 5 to 12 MPa, a range of resistance that had been explored in the initial dataset.

3. RESULTS AND DISCUSSION

A comparison between the 14-day compressive strength and absolute density of the 128 mixes can be seen in Figure 2. These mixes were used to calibrate the ANN.

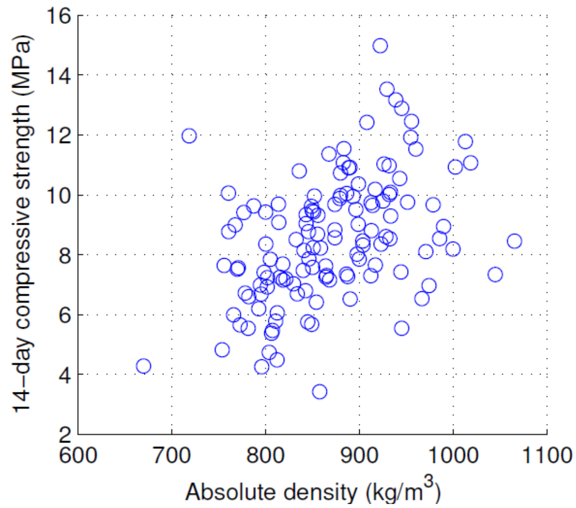

Figure 1: Comparison between the 14-day compressive strength and absolute density of the 128 mixes

The outputs of the ANN were compared with the target values using linear regressions and Pearson's linear correlation coefficients for the training, the testing and the no REGB 0.25 – 0.50 mm datasets, as shown in Figure 3. Results indicate that the ANN was generally good at predicting the 14-day compressive strength of ultra-lightweight concrete.

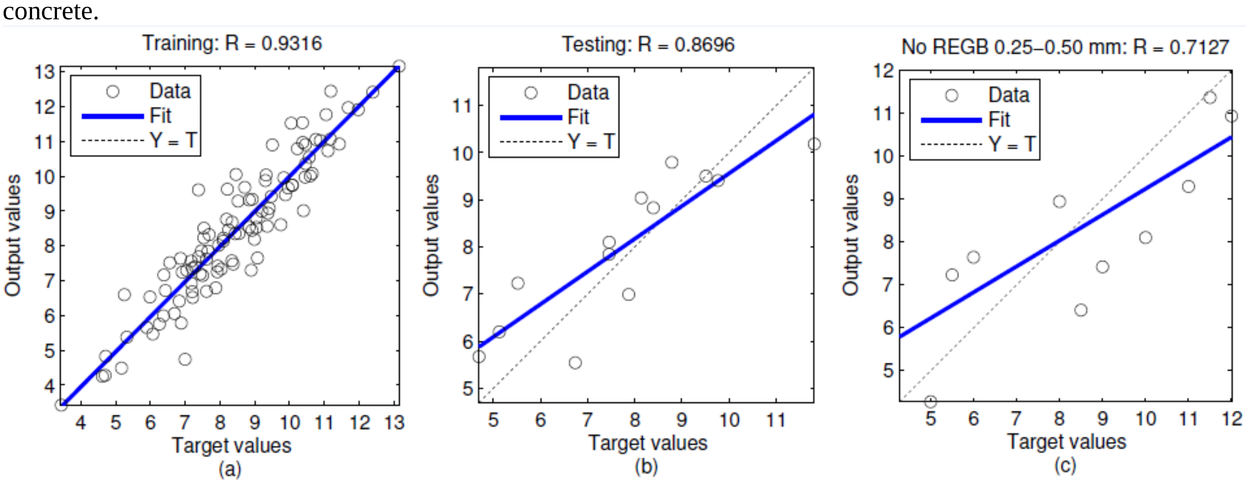

Figure 2: Linear regression and Pearson's linear correlation coefficient of the results for the training dataset (a) and testing dataset (b) used during the calibration process comparing the target and the ANN output values and (c) the comparison for the 11 mixes without REGB 0.25 – 0.50 mm

When comparing the relative error and the performance of the different metrics (Table 3), the Pearson's linear correlation coefficient (r) and normalized root-mean-square error (NMRSE) suggest that the training dataset was very well represented using the ANN (r=0.9316 and NMRSE=0.0749 MPa). While the performance of the testing dataset was a bit lower (r=0.8696 and NMRSE=0.2120 MPa), the ANN still showed good prediction skills. However, for the no REGB 0.25 – 0.50 mm dataset, the r value was lower (r=0.7127 and NMRSE=0.2367), but still showing a fair prediction ability.

Table 3: Comparison metrics results of the target (lab) and output (ANN) values for the training, testing and no REGB 0.25 – 0.50 mm datasets

Training dataset			
No	r	NRMSE (MPa)	R^2
102	0.9316	0.0749	0.9929
Testing dataset			
No	r	NRMSE (MPa)	R^2
13	0.8696	0.2120	0.9855
No REGB 0.25 - 0.50 mm dataset			
No	r	NRMSE (MPa)	R^2
11	0.7127	0.2367	0.9617

When comparing the absolute fraction of variance for the testing dataset (R^2=0.9855) with those obtained with studies on other types of concrete (high-strength concrete: R^2=0.9993 (Öztaş et al., 2006), recycled aggregate concrete: R^2=0.9955 (Duan, Kou et Poon, 2013) and concrete containing metakaolin and silica fume: R^2=0.9985 for ANN-1 and 0.9986 for ANN-2 (Sarıdemir, 2009)), results indicates that the ANN performs at a similar level. The slightly lower value in the R^2 suggests that for ULWC, it might be harder to predict the compressive strength while using an ANN because of the segregation of aggregates due to the density which is lower than that of water and the workability of the mixes.

The relative error was also used as a means of comparison between the target and output values. It was computed using equation 4 where t_j is the target value and o_j is the output value of a time step j.

[4] $$Error = \frac{\left(t_j - o_j\right)}{oj} \times 100$$

In Figure 4, the relative error is illustrated using a bar graph, and the maximum relative error between the target and the output values ranged between -13.75 and 14.50% for the testing dataset and -17.42 to 25.33% for the no REGB 0.25 – 0.50 mm dataset.

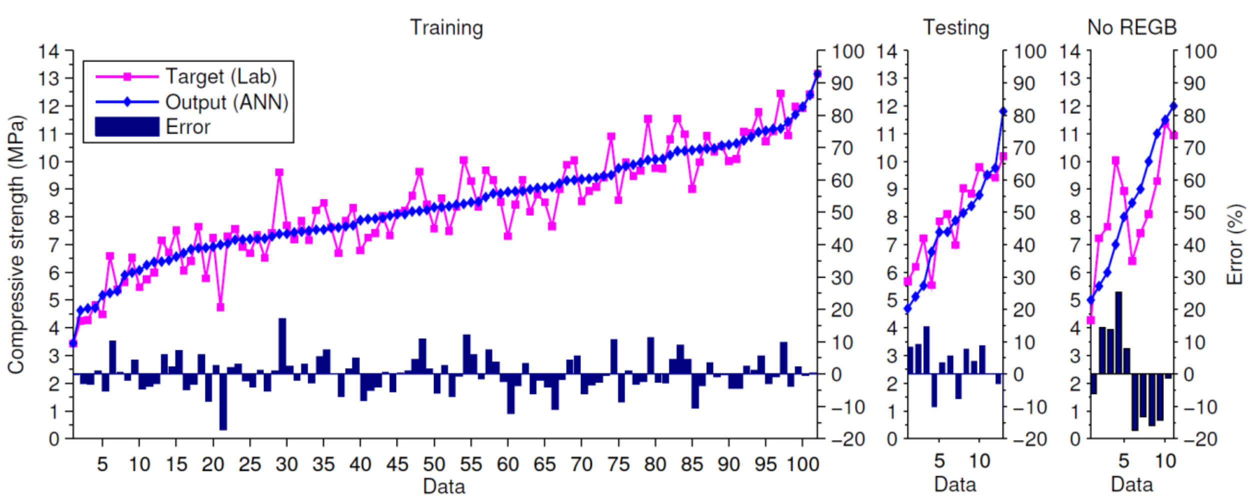

Figure 3: Results for the training, testing and no REGB datasets for both target (lab) and output (ANN) results

The variability in workability of the generated mixes influenced the difference between the predicted compressive strength and the strength tested in the laboratory (Table 4). The dryer mixture prevented lightweight aggregates from undergoing density segregation, and were stronger, while liquid mixtures were weaker. Regarding the no REGB 0.25 – 0.50 mm dataset, the metrics results were not as good as those obtained with the testing dataset. This can be explained by the fact that the ANN was not calibrated on mixes without REGB 0.25-0.50 mm, thus limiting its ability to effect good predictions. However, with a maximum error of 25.33%, the ANN still showed some skills in predicting the 14-day compressive strength in this case.

Table 4: Influence of workability on the gap between measured and predicted compressive strength

Mixture workability	Slump (mm)	F'c gap* (MPa)
Very liquid mixture	≥ 20	-1,4
Liquid mixture	15	-0,2
Normal mixture	10	0,7
Dry mixture	5	1,7
Very dry mixture	0	2,3

*F'c gap = F'c measured - F'c predicted

Since the goal of this work was to help the engineer and the designer as they begin their design optimization process, rather than to replace the entire design phase, tolerating the relative error between the target and output values should not be particularly problematic. The mix suggested by the ANN is a much better baseline mix than what obtains using traditional methods (e.g., iterative methods) and the designer's experience.

An advantage of the ANN is the possibility of generating mixes answering the designer's objectives other than compressive strength. As the carbon footprint is becoming a decisive argument in infrastructure decision making (Purnell et Black, 2012), the embodied carbon was calculated for the generated mixes, and a lower embodied carbon was found for ultra-lightweight concrete with a higher compressive strength. Subsequently, the designer can choose the mix that corresponds to his objectives (e.g., carbon footprint, absolute density, polymer content, cost, as well as different estimated rheological properties) from this dataset. In this work, one million mixes were generated, with 14-day compressive strength ranging from 5 to 12 MPa. As shown in Figure 5, a vast range of possible carbon footprints and absolute densities can be obtained for a given compressive strength. A multi-objective optimization could also be performed if the designer has more than one objective.

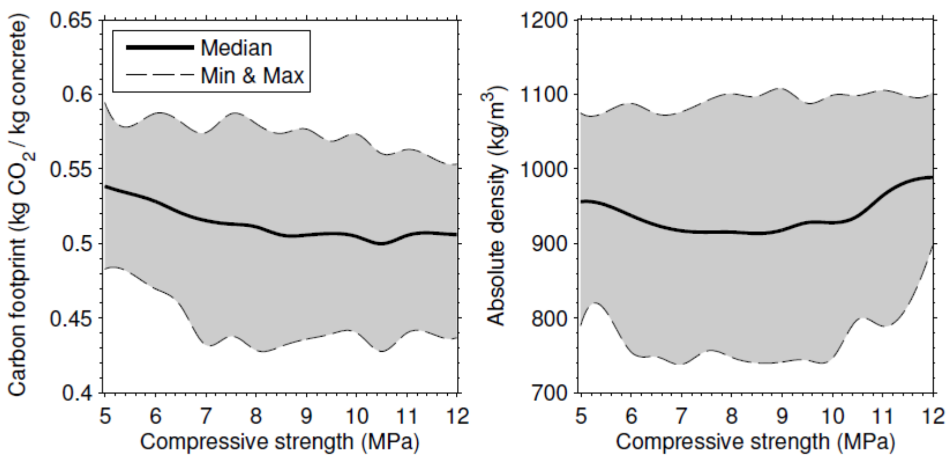

Figure 4: Comparison of the 14-day predicted compressive strength against carbon footprint and absolute density using ULWC generated with the proposed ANN

By using the genetic algorithm, a virtually unlimited range of ULWC mixes can be generated answering the designer's objectives, and tested until a mix with a desired workability is obtained. Using the designer's experience, combined with the theory underlying concrete mixes, the workability of the mix can be controlled. Material constraints can be added based on size, surface and angularity index (Alexander et Mindess, 2010) in order to control the water requirement for a workable mix. For example, the glass microsphere is 40 µm and spherical, which lubricates and improves the workability of the mixes. As well, GBFS reduces the water demand and improves the workability (Kosmatka et al., 2011). On the other hand, recycled expanded glass beads are known for their high water absorption (20% on average), which reduces the fluidity of the mix for the same water amount. Different constraints can therefore be added during the generation of the mixes to attain the desired workability.

4. CONCLUSION

An ultra-lightweight concrete (ULWC) was made from general use white Portland cement, granulated blast furnace slag, two sizes of recycled expanded glass bubbles, glass microspheres, acrylic and SBR latex emulsions and a polycarboxylate superplasticizer. An artificial neural network (ANN) predicted the 14-day compressive strength of ULWC using 13 constraints and boundary conditions for each material. The database included 128 mixes generated from the ANN. 102 mixes were used for the calibration, 13 for the validation and 13 for testing the ANN. The ANN showed a strong capacity to predict the 14-day compressive strength of ULWC, which was better than expected. However, the ANN did not always predict workable mixes, because its respective constituents have different effects on the fluidity of the fresh mix, depending on their proportions. Precise constraints and boundary conditions are needed to ensure a lower variability in workability. The ANN, coupled with a genetic algorithm, can generate millions of mixes for a given compressive strength in a short amount of time. Thus, the designer can choose the mixes that correspond to his additional objectives.

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REFERENCES

Alexander, M., et S. Mindess. 2010. *Aggregates in Concrete*. CRC Press, 448 p.

Alshihri, Marai M., Ahmed M. Azmy et Mousa S. El-Bisy. 2009. « Neural networks for predicting compressive strength of structural light weight concrete ». *Construction and Building Materials*, vol. 23, nº 6, p. 2214-2219.

American Concrete Institute. 2005. *Specification for Structural Concrete*. Farmington Hills: American Concrete Institute, 656 p.

ASTM. 2014a. *C39 / C39M-14a, Standard Test Method for Compressive Strength of Cylindrical Concrete Specimens*. ASTM International: West Conshohocken, PA. < http://www.astm.org/ >.

ASTM. 2014b. *C192 / C192M-14, Standard Practice for Making and Curing Concrete Test Specimens in the Laboratory*. West Conshohocken, PA: ASTM International. < http://www.astm.org/ >.

Baykasoğlu, Adil, Ahmet Öztaş et Erdoğan Özbay. 2009. « Prediction and multi-objective optimization of high-strength concrete parameters via soft computing approaches ». *Expert Systems with Applications*, vol. 36, nº 3, p. 6145-6155.

Bilim, Cahit, Cengiz D. Atiş, Harun Tanyildizi et Okan Karahan. 2009. « Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network ». *Advances in Engineering Software*, vol. 40, nº 5, p. 334-340.

Duan, Z. H., S. C. Kou et C. S. Poon. 2013. « Prediction of compressive strength of recycled aggregate concrete using artificial neural networks ». *Construction and Building Materials,* vol. 40, nº 0, p. 1200-1206.

Hecht-Nielsen, R. 1989. « Theory of the backpropagation neural network ». In *Neural Networks, 1989. IJCNN., International Joint Conference on*. (0-0 1989), p. 593-605 vol.1.

Kosmatka, Steven H., Beatrix Kerkhoff, Doug Hooton et Richard J. McGrath. 2011. *Dosage et Contrôle des Mélanges de Béton, EB101, 8th edition*. Ottawa: Association Canadienne du Ciment, 421 p.

Özcan, Fatih, Cengiz D. Atiş, Okan Karahan, Erdal Uncuoğlu et Harun Tanyildizi. 2009. « Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete ». *Advances in Engineering Software,* vol. 40, nº 9, p. 856-863.

Öztaş, Ahmet, Murat Pala, Erdogˇan Özbay, Erdogˇan Kanca, Naci Çagˇlar et M. Asghar Bhatti. 2006. « Predicting the compressive strength and slump of high strength concrete using neural network ». *Construction and Building Materials,* vol. 20, nº 9, p. 769-775.

Purnell, Phil, et Leon Black. 2012. « Embodied carbon dioxide in concrete: Variation with common mix design parameters ». *Cement and Concrete Research,* vol. 42, nº 6, p. 874-877.

Sarıdemir, Mustafa. 2009. « Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks ». *Advances in Engineering Software,* vol. 40, nº 5, p. 350-355.

Sobhani, Jafar, Meysam Najimi, Ali Reza Pourkhorshidi et Tayebeh Parhizkar. 2010. « Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models ». *Construction and Building Materials,* vol. 24, nº 5, p. 709-718.

Sohel, K. M. A., J. Y. Richard Liew, J. B. Yan, M. H. Zhang et K. S. Chia. 2012. « Behavior of Steel–Concrete–Steel sandwich structures with lightweight cement composite and novel shear connectors ». *Composite Structures,* vol. 94, nº 12, p. 3500-3509.

Xu, Yi, Linhua Jiang, Jinxia Xu et Yang Li. 2012. « Mechanical properties of expanded polystyrene lightweight aggregate concrete and brick ». *Construction and Building Materials,* vol. 27, nº 1, p. 32-38.

Yeh, I. Cheng. 2007. « Modeling slump flow of concrete using second-order regressions and artificial neural networks ». *Cement and Concrete Composites,* vol. 29, nº 6, p. 474-480.