Properties prediction of environmentally friendly ultra-high-performance concrete using artificial neural networks

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ABSTRACT

Ultra-high-performance concrete (UHPC) results from the mixture of several constituents, leading to a highly complex material in both, fresh and hardened state. The higher number of constituents, together with a higher number of possible combinations, relative proportioning and characteristics, makes the behavior of this type of concrete more difficult to predict. The objective of the research is to build four analytical models, based on artificial neural networks (ANN), to predict the 1-day, 7-day, and 28-day compressive strengths and slump flow. Recycled glass powder milled to different particle size, fluid catalytic cracking residue (FCC) and different particle size limestone powder was used as partial replacements for Portland cement and silica fume. The ANN models predicted the 1-day, 7-day, and 28-day compressive strengths and slump flow of the test set with prediction error values (RMSE) of 2.400 MPa, 2.638 MPa, 2.064 MPa and 7.245 mm respectively. The results indicated that the developed ANN models are an efficient tool for predicting the slump flow and compressive strengths of UHPC while incorporating silica fume, limestone powder, recycled glass powder and FCC.

KEYWORDS

UHPC; ANN; compressive strength; slump flow; SCM; virtual packing density

1. Introduction

Ultra-high performance concrete (UHPC) is a new type of concrete that is characterized by its high compressive strength and excellent durability (Abellán et al., 2018b, 2018a; Ghafari, Bandarabadi, et al., 2015; Zhang & Zhao, 2017). The enhanced durability of UHPC can particularly benefit infrastructure that undergoes serious environmental loadings (Abellán et al., 2018b). Other benefits of using UHPC include reducing the amount of concrete needed in a structure, which in turn increases the overall net space, reduces labor and equipment needed for precast element's erection, and reduces the construction time (Ghafari, Costa, et al. 2015; Zhang & Zhao, 2017). However, owing to the absence of a coarse aggregate together with its high packing density, UHPC contents of cement, quartz sand, quartz powder and silica fume used are high, increasing the cost of UHPC and providing a great environmental impact (Abellán-García et al., 2019; Abellán et al., 2020; Meng et al., 2018). Therefore, considering those disadvantages that restrict its wider usage, some industrial by-products such as recycled glass powder (GP) and fluid catalytic cracking residue (FCC) as well as other supplementary cementitious materials (SCM) such as limestone powder (LP) have been used as partial replacements for cement, quartz powder and silica fume, whose cost are higher than cement. For example, the behavior of dosages of UHPC containing fly ash (FA), silica fume (SF) and fluid catalytic cracking residue (FCC), a by-product of the crude oil industry, was analyzed

(Camacho et al., 2012; Camacho Torregrosa, 2013). The research showed the possibility of a partial replacement of cement and silica fume. Incorporating limestone powder in UHPC improved the hydration process at the early-age, producing denser particle packing, and improving mechanical properties (Li et al., 2016). Even nano- CaCO_3 was used as a component of binder (Huang & Cao, 2012). A 17% increase in compressive strength was observed, compared to the UHPC control specimens without nano- CaCO_3 . The results of the partial substitution of silica fume with fine glass powder (FGP) in UHPC were analyzed (Soliman & Tagnit-Hamou, 2017a). They demonstrated that compressive strength values of 235 and 220 MPa under 2 days of steam curing can be achieved when replacing 30% and 50% of SF with FGP respectively, with a mean particle size (d_{50}) of $3.8\text{ }\mu\text{m}$. However, the amount of cement used exceeded 800 kg/m^3 . In another study recycled glass powder was used to replace quartz sand, cement and quartz powder particles (Soliman & Tagnit-Hamou, 2017b; Tagnit-Hamou et al., 2016a). These investigations showed that it is possible to replace significant amounts of cement and silica fume in UHPC mixes with other SCM while keeping the amount of water added constant, without significantly decreasing the compressive strength.

However, the essential properties of UHPC with SCMs need to be validated experimentally because of the unclear combination effects of different materials and dosages being used in the mixture. Laboratory experiments are often costly, time-consuming, and labor-intensive (Zhang & Zhao, 2017). To minimize the experimental workload of property assessment and mix design, probabilistic models can be successfully employed to forecast the properties of concrete, yet these cannot be applied where in the modeling problem involves many independent variables or the interactions among the variables is either unknown or too complex to represent (Chandwani et al., 2015; Ghafari, Bandarabadi, et al., 2015; Zhang & Zhao, 2017). In the case like the UHPC, because of the large volume of SCMs, the use of traditional techniques of regression fails to yield the expected accuracy and predictability (Chandwani et al., 2015).

In the past few decades, the nature inspired computational tool Artificial Neural Network (ANN), has been used for modeling the real-world problems due to its immense ability to capture inter-relationships among input and output data pairs which are unknown, nonlinear or too difficult to formulate, demonstrating its effectiveness in solving difficult and complex engineering problems (Khashman & Akpinar, 2017).

Hence, ANN models have been employed in many civil engineering applications like traffic engineering, water resources engineering, detection of structural damage, structural system identification, material behavior modeling, concrete mix proportioning and concrete strength prediction (Adeli, 2001; Aderaw et al., 2018). Moreover, one of the most fertile fields in the specialized literature of civil engineering production, is the application of ANN to predict mechanical properties of pastes, mortars and concretes (Chandwani et al. 2014). Aderaw et al. (2018) constructed an ANN model with a single hidden to predict the compressive and tensile splitting strength of concrete incorporating agricultural and construction wastes. Several studies (Duan et al., 2013; Sahoo et al., 2016) used ANN for predicting the compressive strengths of recycled aggregate concrete. (Jamalaldin et al., 2011) developed an ANN's model to predict the compressive strength of high strength concrete using silica fume, fly ash and granulated graded blast furnace slag as SCM. Their ANN model was able to predict experimental results accurately. Torre et al. (2015) also constructed a multilayer perceptron model to predict compressive strength of high-performance concrete. The model accurately predicted the compressive strength of concrete. Other applications of ANN modeling for concrete, includes training the data for several epochs (Kalra & Joseph, 2016). They built a multi-layer feed-forward ANN architecture for predicting the compressive strength of concrete. According to the research, the best validation performance was reached at epoch 40 with a mean squared error value of 10.99 MPa. Notable among other studies are successful implementations in predicting and modeling different properties of self-compacting concrete (Bharathi et al., 2017; Uysal & Tanyildizi, 2012), fiber reinforced concrete (FRP)-confined concrete (Naderpour et al., 2010), rubberized concrete (Abdollahzadeh et al., 2011), compressive strength of concrete containing Nano-Silica (Gupta, 2013), durability of high performance concrete (Parichatprecha & Nimityongskul, 2009), estimating compressive strength of ferrocement concrete (Khan & Ayub, 2013), predicting drying shrinkage of concrete (Bal & Buyle-Bodin, 2013), and prediction of elastic modulus of normal and high strength concrete (Demir, 2008).

On the other hand, little research has been conducted on predicting the performance of UHPC using ANN. Ghafari, Bandarabadi, et al. (2015) built two analytical models based on artificial neural networks (ANNs) and statistical mixture design (SMD) method to predict the required performance of ultra-high-

Table 1. Previous research about the prediction of the performance of UHPC using ANN.

Reference	SCMs	Activation function	Architecture	Number of observations in data	Output(s)
Taghaddos et al. (2004)	SF	Fuzzy logic function	4-2-2-1	38	12 day compressive strength under heat treatment
Ghafari et al. (2015)	SF, QP	Log-sigmoid	7-15-3	53	Slump Flow, 28 day compressive strength, 2 day compressive strength under heat treatment
Zhang and Zhao (2017)	SF, FA	Tan-sigmoid	11-10-4	78	7, 28, 90 and 365 day compressive strength

performance concrete (UHPC) with two different curing conditions. They concluded that compared with traditional statistical methods, the ANN model could predict the compressive strength with higher accuracy because of its distributed and nonlinear nature. Taghaddos et al. (2004) presented the application of an adaptive neuro fuzzy inference system (ANFIS) to predict compressive strength behaviour of UHPC while considering mix design and curing conditions. The incorporation of SCM such as fly ash (FA) and silica fume has been studied through an ANN model (Zhang & Zhao, 2017). The model provided a highly accurate method for predicting the compressive strength of UHPC containing FA and SF. Table 1 summarizes the only three projects research available about UHPC using ANN.

However, how to find an accuracy model to predict the mechanical and rheological properties of UHPC incorporating several SCMs of a different nature using ANN, remains an open question.

Therefore, the main objective of this study was to fill that gap. In order to avoid the loss of accuracy for any response when a multi output model is used (Chollet & Allaire, 2018), a different model was developed for each response. Four analytical models were developed, based on artificial neural networks (ANN), to predict the 1-day, 7-day, and 28-day compressive strengths and slump flow of UHPC containing different SCMs, such as silica fume (SF), fluid catalytic cracking residue (FCC), limestone powder, micro-limestone powder, recycled glass powder, recycled glass flour and quartz flour (QF). A total of 265 experimental results of concrete mixtures with different combinations of those SCM (see Appendix A) were used for the training and testing of ANN models.

2. Materials and methods

2.1. Materials

Materials used for this study were ordinary Portland cement type I 42.5 N, condensed silica fume, fluid catalytic cracking residue, limestone powder, micro-limestone powder, recycled glass powder, recycled glass flour, quartz flour, silica sand, polycarboxylate ether-based superplasticizer and water. The detailed information of used materials is summarized in Figures 1 and 2, and Table 2.

2.2. Experimental methodology

The mixture design involved several steps. The amounts of cement, water, and superplasticizer were determined by a three-factor Design of Experiments (DoE). The other components were ruled by the $A \& A_{mod}$ curve (Funk & Dinger, 1994) according to Equation (1).

$$P(D) = \frac{(D^q - D_{min}^q)}{(D_{max}^q - D_{min}^q)} \quad (1)$$

where D is the particle size, $P(D)$ is the weight fraction of total solids that are smaller than D , D_{max} and D_{min} are the maximum and minimum particle sizes, respectively, and q is the Fuller exponent. The optimal value of q was determined in previous research (Abellan et al., 2018a), however the database includes all the dosages needed to reach that optimal, viz. there are several values of q in the dosages of the train and test set.

Experimental results of a total of 265 concrete mixtures with different SCMs and combinations according to Appendix A were used for the training and testing of ANN models.

Figure 1. Materials used in this research: (a) Cement I 42.5 R; (b) condensed silica fume; (c) FCC; (d) micro limestone powder ($d_{50} = 2 \mu$); (e) limestone powder ($d_{50} = 16 \mu$); (f) recycled glass powder ($d_{50} = 7 \mu$); (g) recycled glass flour ($d_{50} = 28 \mu$); (h) quartz flour; and (i) silica sand.

Figure 2. Particle size distribution of the used materials.

In preparing specimens, a 5-liter mortar type laboratory mixer was used. After the mixing was completed, tests were immediately conducted, still in a fresh state, to determine static slump flow diameter in accordance with ASTM 1437 specifications (ASTM and ASTM C1437, 2016). In the slump flow test, a truncated conic mold was placed on a smooth plate, filled with UHPC, and lifted upward. The spread diameter of the mortar was measured in four perpendicular directions, and the average of the diameters was reported as the spread flow of the concrete ($\varnothing_m$) in mm.

Table 2. Chemical properties of materials.

Chemical analysis	Cement	Silica fume	FCC	Limestone powder	Recycled glass	Quartz powder	Silica sand
SiO ₂ , %	19.42	92.29	39.61	0.90	72.89	95.80	99.80
Al ₂ O ₃ , %	4.00	0.59	42.47	0.10	1.67	0.11	0.14
CaO, %	64.42	3.89	2.85	55.51	9.73	0.38	0.17
MgO, %	1.52	0.26	0.07	0.70	2.08	0.20	0.01
SO ₃ , %	1.93	0.07	0.62	0.10	0.01	0.52	–
Na ₂ O, %	0.19	0.31	0.61	0.03	12.54	0.25	–
K ₂ O, %	0.39	0.54	0.06	0.00	0.76	3.49	0.05
TiO ₂ , %	0.38	0.01	0.67	0.00	0.04	0.25	0.02
Mn ₃ O ₄ , %	0.05	0.01	0.00	0.01	0.01	0.01	–
Fe ₂ O ₃ , %	3.61	0.24	0.69	0.05	0.81	0.09	0.04
Lossofignition, %	2.58	0.60	10.61	42.21	1.00	0.31	0.19
Specificgravity, gr/cm ³)	3.16	2.20	2.76	2.73	2.55	2.65	2.65

Figure 3. Schematic diagram of perceptron structure.

After mixing, concrete was poured in a mold and, 24 hours later, the specimens were demolded. Then, the specimens were cured in a moisture room at 20 °C until the day of the test without any heat treatment applied. In order to determine the compressive strength, 50 mm cubes were tested. A concrete compression machine with 3000 KN in capacity was used following ASTM C109 (ASTM, 2010). Three samples were tested for each different age: 24 hours, 7 days, and 28 days to determine the 1-day compressive strength (f_{1d}), 7-day compressive strength (f_{7d}), and 28-day compressive strength (f_{28d}).

2.3. Analytical methodology

2.3.1. Artificial neural networks

ANN are composed of many highly interconnected processing elements (neurons) working together (Adeli, 2001). Each node is fully connected to the other through connection weights and receives an input signal from neurons linked to it. The successive layers of nodes receive input from the previous layers; the outputs of nodes in each layer are inputs to nodes in the next layer. The simplest form of ANN architecture is the perceptron, devised by (Rosenblatt, 1958), which consists of one neuron with two inputs and one output (Ghafari & Al, 2012). Perceptron is defined as a four-tuple entity (i.e., sensors that (i) receive inputs and (ii) multiply them by weights, (iii) a function collecting all the weighted data to produce a measurement on the impact of the observed phenomenon, and (iv) a constant threshold). Adjusting these weights to produce a particular output is called ‘training’, which is the mechanism that allows the network to learn (Estebon, 1997). The schematic diagram of perceptron structure is depicted in Figure 3.

The $x_i = (x_1, x_2)$ vector represents an input link applied to each neuron. A bias is also added to the neuron along with inputs. $w_i = (w_1, w_2)$ represents the weights for each input. The weighted sum function computes the net input that approaches to a neuron (Anderson, 1983). The weighted sums of the input components (i.e., the sum function) are computed by using Equation (2) as follows:

Figure 4. Schematic representation of the architecture of a two hidden layer MLP with back propagation.

$$v_j = \sum_{i=1}^n w_{ij}x_i + b \quad (2)$$

where v_j is the weighted sum of the j th neuron for the input received from the preceding layer, with n neurons, w_{ij} is the weight between the j th neuron and the i th neuron in the preceding layer; x_i is the output of the i th neuron in the preceding layer and b is a constant (Bharathi et al., 2017).

The activation function processes the net input obtained from the sum function and determines the neurons output. Some activation functions examples include step, linear, ramp, hyperbolic tangent, log-sigmoid functions and *relu* (rectified linear unit function) (Chollet & Allaire, 2018). In this work we use the log-sigmoid activation function. The log-sigmoid function takes the input, which can have any value between minus and plus infinite and squashes the output in the range 0 to 1 (Demir, 2008).

Rumelhart et al. (1986) developed the most commonly used learning algorithm called back-propagation (BP) for perceptron networks with hidden units. The learning algorithm consists of two main steps: (i) A forward signal flow from the input layer to the output layer is sent and the result of the output layer, $\hat{a}_j$, is compared to the target (train data) value a_j . The error of each output neuron is determined by the difference between the computed values and the target values from the train data so that the resulting error is propagated backward, and the network's weights are calculated to minimize the overall error; (ii) Readjustment of the weights and biases in the hidden and output layers to reduce the difference between the computed and desired outputs is performed using a 'generalized delta rule' through the gradient descent on the error. The training process is performed iteratively until the loss function which measures the differences between the actual and the desired outputs is minimized.

For more complex applications, multi-layer perceptrons (MLP) are used, which contain one input layer, one output layer, and one or more hidden layers as shown in Figure 4. The multilayer perceptron (feed-forward network) has been a commonly used ANN architecture (Aderaw et al., 2018; Chandwani et al., 2015; Gupta, 2013).

In order to simplify the learning process of the back-propagation neural network and to reduce the required training time, the learning algorithm adopted to train the network model in this study is the Resilient back propagation algorithm (Rprop).

2.3.2. Preparing training and tests set

A two-hidden-layer perceptron was created using R version 3.5.2 (2018-12-20) and Keras version 2.2.4. R is a language and environment for statistical computing and graphics (R Core Team, 2018). On the other

Table 3. Statistical parameters of training, test and total data sets.

	Training		Test		Total	
	Min.	Max.	Min.	Max.	Min.	Max.
1. Input parameters						
Cement, C [m ³ /m ³]	0.152	0.364	0.156	0.312	0.152	0.364
Silica Fume, SF [m ³ /m ³]	0	0.225	0	0.220	0	0.225
Recycled Glass Powder, GP [m ³ /m ³]	0	0.202	0	0.202	0	0.202
Fluid Catalytic Residue, FCC [m ³ /m ³]	0	0.176	0	0.160	0	0.176
Limestone Powder, LP [m ³ /m ³]	0	0.137	0	0.135	0	0.137
Quartz Powder, QP [m ³ /m ³]	0	0.228	0	0.220	0	0.228
Superplasticizer, PCE [m ³ /m ³]	0.005	0.057	0.01	0.052	0.005	0.057
Water, W [m ³ /m ³]	0.142	0.262	0.155	0.260	0.142	0.262
Water to binder ratio, WB	0.125	0.300	0.130	0.310	0.125	0.310
Water to total powders ratio, WP	0.120	0.310	0.119	0.310	0.119	0.310
Silica Sand in volume, SS [m ³ /m ³]	0.200	0.563	0.200	0.550	0.200	0.563
Virtual Packing Density, VPD	0.610	0.861	0.625	0.856	0.610	0.861
2. Output parameters						
Slump Flow, $\emptyset_m$ [mm]	100	410	100	405	100	410
1-day compressive strength, f_{1d} [MPa]	18.90	125.54	12.45	110.56	12.45	125.54
7-day compressive strength, f_{7d} [MPa]	46.00	152.44	47.23	151.32	46.00	152.44
28-day compressive strength, f_{28d} [MPa]	69.36	172.70	71.45	162.23	69.36	172.70

hand, Keras is a high-level neural networks application, written in Python and capable of running on R language (Chollet & Allaire, 2018). A total of 400 Artificial networks were constructed for each response (1600 in total) using 265 experimental datasets obtained from the experimental works. The networks were composed of input neurons (input layer), computational neurons (hidden layer) and an output layer. Twelve input signals/variables used are volume of cement (C), silica fume (SF), recycled glass powder (GP), which includes the sum of the volumes of recycled glass powder ($d_{50} = 7 \mu$) and recycled glass flour ($d_{50} = 28 \mu$), Fluid Catalytic Cracking Residue (FCC), Limestone Powder (LP) which includes the sum of the volumes of limestone powder ($d_{50} = 15 \mu$) and micro limestone powder ($d_{50} = 2 \mu$), quartz powder (QP), polycarboxylate ether based superplasticizer (PCE), water (W), water to binder ratio (WB) which contemplates the relationship between the water and the powders with pozzolanic properties, water to total powders ratio (WP), silica sand (SS) and virtual packing density (VPD) according to the compressive packing model (De Larrard, 1999). The 1-day compressive strength (f_{1d}), 7-day compressive strength (f_{7d}), 28-day compressive strength (f_{28d}) and the slump flow ($\emptyset_m$) were used as target, while the predicted values were denoted as $\hat{f}_{1d}$, $\hat{f}_{7d}$, $\hat{f}_{28d}$ and $\hat{\emptyset}_m$ respectively. Table 3 presents the range of input and output parameters.

The VPD was calculated according to the compressive packing model theory (De Larrard, 1999). The general equation, which represents the virtual packing density (VPD) of a granular mix containing n materials classes, when class i is dominant, is given by Equation (3).

$$VPD = \text{Min} \left\{ \frac{\beta_i}{1 - \sum_{j=1}^{i-1} \left[1 - \beta_j + b_{ij} \beta_j \left(1 - \frac{1}{\beta_j} \right) \right] y_j - \sum_{j=i+1}^n \left[1 - \frac{a_{ij} \beta_j}{\beta_i} \right] y_j} \mid i = 1, \dots, n \right\} \quad (3)$$

where:

VPD: Virtual packing density of an n component polydisperse mix according to compressive packing model theory (De Larrard, 1999)

β_i : Residual packing density of a monodisperse fraction having a diameter equal to d_i

d_i : Diameter of i th class of particles. When $i > j$, $d_i < d_j$

a_{ij} : Parameter describing the loosening effect exerted by class j on the dominant class i . See Equation (4).

b_{ij} : Parameter describing the wall effect exerted by class j on the dominant class i . See Equation (5).

y_i : Volume fraction of the i th class, related to the total solid volume

$$a_{ij} = \sqrt{1 - \left(1 - \frac{d_j}{d_i} \right)^{1.02}} \quad (4)$$

Table 4. Residual packing density for each component.

Residual packing density (β)								
Cement	SF	FCC	Micro limestone powder	Limestone powder	Recycled glass powder	Recycled glass powder	Quartz flour	Silica sand
0.553	0.720	0.551	0.553	0.549	0.554	0.548	0.565	0.550

$$b_{ij} = 1 - \left(1 - \frac{d_i}{d_j}\right)^{1.50} \quad (5)$$

The residual packing density of each component is shown in [Table 4](#).

To facilitate training and testing of the neural networks, the collected data was randomized and split into training and test datasets. 200 observations were used for training purposes and the remaining 65 were used for testing of the trained ANN. Both subsets must contain all the possible components in the mixture.

2.3.3. Preprocessing the data

The input data and output data generally comprise of different identities either having no or minimum similarities. Preprocessing or normalization of data eliminates the possibility of neural network bias towards the different identities and scales down all the input and output data. Linear scaling in the range [0, 1] has been used in the present study having function as depicted in [Equation \(6\)](#).

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

where x_{norm} is the normalized value of the variable x , x_{max} and x_{min} are the minimum and maximum values of variable x respectively.

2.3.4. Network training

Back Propagation and its variations are widely used as methods for training artificial neural networks. One such variation, Resilient Back Propagation (Rprop), has proven to be one of the best in terms of speed of convergence (Naoum & Al-Sultani, 2013). Resilient propagation and back propagation are very much similar, except for the weight update routine (Prasad et al., 2013). Resilient propagation does not take into account the value of the partial derivative (error gradient), but rather, considers only the sign of the error gradient to indicate the direction of the weight update. Back propagation is slow at converging due to the gradients having a very small magnitude, which causes small changes in weight. The purpose of Rprop training algorithm is to eliminate the harmful effects of these magnitudes of the partial derivatives. Only the sign of the derivative can determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. Another most difficult aspect of the back propagation learning was picking the correct training parameters. Resilient propagation does have training parameters, but it is extremely rare that they need to be changed from their default values. This makes resilient propagation a very easy way to use a training algorithm. It also has the nice property that it requires only a modest increase in memory requirements. As consequence Rprop is one of the fastest training algorithms available (Mushgil et al., 2015).

In this study, the ANN's models were trained using log-sigmoid defined in [Equation \(7\)](#) as activation function and resilient back propagation (Rprop) as learning algorithm.

$$\text{Log - sigmoid : } g(x) = \frac{1}{1 + e^{-x}} \quad (7)$$

The network training was made layer by layer doing forward and backward computations (Aderaw et al., 2018). During the learning algorithm process, the update values and the weights are changed every time the whole pattern set has been presented once to the network (learning by epoch). For further information about Rprop, see (Mushgil et al., 2015).

2.3.5. Model performance evaluation

The ANN model was trained on the training data and measures of accuracy, and then using the prediction errors on that validation set. The model's predictive accuracy was measured through computing mean absolute error (MAE), normalized mean bias error (NMBE) and coefficients of multiple determination (R^2), using Equations (8)–(11) respectively.

$$MAE = \frac{1}{n} \sum_{i=1}^n |a_i - \hat{a}_i| \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (a_i - \hat{a}_i)^2}{n}} \quad (9)$$

$$NMBE(\%) = \frac{\frac{1}{n} \sum_{i=1}^n (a_i - \hat{a}_i)}{\bar{a}_i} \times 100 \quad (10)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (a_i - \hat{a}_i)^2}{\sum_{i=1}^n (\hat{a}_i)^2} \quad (11)$$

where: a is the target or experimental value; $\bar{a}$ represents the mean observed target, $\hat{a}$ is the predicted value or model's output and n is the total number of observations in the current data.

MAE uses absolute differences between the measured and the predicted values. The optimal value of MAE is zero (Aderaw et al., 2018); RMSE is one of the commonly used error index statistics (Moriassi et al., 2007). RMSE compares the observed values to the predicted values and computes the square root of the average residual error, indicating error in the units (or squared units) of the constituent of interest, which aids in analysis of the results. RMSE values of zero indicate a perfect fit. However RMSE gives more weightage to large errors (Chandwani et al., 2015); The NMBE provides information on the mean bias in the predictions from a model. A positive NMBE indicates over-prediction and a negative NMBE indicates under-prediction of the model (Srinivasulu & Jain, 2006); Coefficient of determination (R^2) compares the accuracy of the model with the accuracy of a superficial benchmark model wherein the prediction is the mean of all samples (Gupta, 2013). R^2 statistics is dependent on the linear relationships between the observed and predicted values and may sometimes give biased results when this relationship is not linear or when the values contain many outliers. A R^2 value close to unity indicates perfect association between the observed and predicted values. A combined use of the performance metrics narrated above can provide an unbiased estimate for prediction ability of the neural network models.

2.3.6. K-fold validation

To evaluate the network while keeping adjusting its parameters (such as the number of epochs used for training), the training data could be split into a training set and a validation set. However, because there are such few data points, the validation set would end up being very small (in our case, about 50 examples). Therefore, the validation scores might change a lot depending on which data points were chosen to use for validation and which were chosen for training: that is, the validation scores might have a high variance with regard to the validation split. This would prevent from reliably evaluating the model (Chollet & Allaire, 2018).

The best practice in such situations is to use K-fold cross-validation (see Figure 5). It consists of splitting the available data into K partitions, instantiating K identical models, and training each one on K – 1 partitions while evaluating the remaining partition. The validation score for the model used is then the average of the K validation scores obtained (Chollet & Allaire, 2018).

In this study K=4 was considered.

2.3.7. ANN architecture design

Determining ANN architecture is the first important step in developing an ANN model that best suits the problem at hand. However, there is no guideline for selecting the optimum ANN architecture. In this research four-layer perceptron was created using R version 3.5.2 (2018-12-20) and Keras version 2.2.4. The selection of hidden layers and hidden layer neurons is a trial and error process and generally started by

Figure 5. K-fold validation (Chollet & Allaire, 2018).

choosing a network with a minimum number of hidden layers and hidden neurons (Chandwani et al., 2015). For arriving at optimal neural network architecture, a total of 400 Artificial networks were constructed for each response and validated using K-fold validation to find the best one. The RSME was used as measure of accuracy.

In this step the total training data are 10 time passed from the network (10 epochs), selecting the epoch with minimum RMSE in the K-fold validation procedure (as average of the 4 validation sets). Once the number of hidden neurons in each layer is selected, the model will be trained until 500 epochs, for selecting the best performance number of it.

Once all parameters of the model are fixed (i.e. architecture and number of epochs), a final production model could be trained on all of the training data, with the best parameters, and then look at its performance on the test data.

3. Results and discussion

3.1. ANN architectures

Figure 6 represents the RMSE versus the number of hidden neurons in first and second hidden layer for each response in both validation and training sets using K-fold validation limiting the number of epochs at 10. The graph also shows the global minimum RSME value in the validation set (left) and its corresponding value in the training set (right).

As expected, for all models, the training set performance improved as the number of hidden neurons increases, because the overfit.

Consequently, according to the aforementioned procedure, the network architectures shown in Figure 7 were selected.

3.2. Number of epochs for each model

Once the architecture is selected, the next step is to fix the number of epochs for each model. Figure 8 depicts a smoothed curve of RSME measure in the K-validation set versus number of epochs in all cases.

According to this plot, validation RSME stopped improving significantly after 156, 161, 144 and 137 epochs for $\hat{\theta}_m$, $\hat{f}_{1d}$, $\hat{f}_{7d}$, and $\hat{f}_{28d}$ respectively. Past these points, the models started overfitting.

Once all parameters of the model are fixed, a final production model could be trained on the complete training data, with the best parameters, and then look at its performance on the test data. Results are depicted in Figures 9–12.

It can be noticed in Figures 9–12 that the slump flow and different age compressive values generated by the models were very close to those of test set counterparts. The correlation (R^2) measured on the test data set indicates the accuracy of the models. On the other hand, the high correlation presented are consistent with those obtained by other authors consulted, who obtained correlation coefficients between 0.96 and 0.98 when predicting UHPC's properties using ANN (Ghafari, Bandarabadi, et al., 2015; Zhang & Zhao, 2017).

(a) L12-10-5-1 model for $\hat{\theta}_m$

(b) L12-9-5-1 model for $\hat{f}_{1d}$

(c) L12-4-2-1 model for $\hat{f}_{7d}$

(d) L12-4-4-1 model for $\hat{f}_{28d}$

Figure 6. RMSE versus the number of hidden neurons in first and second hidden layer in both validation (left) and training (right) sets for each response: (a) slump flow; (b) 1-day compressive strength; (c) 7-day compressive strength; and (d) 28-day compressive strength.

(a) L12-10-5-1 model for $\hat{O}_m$

(b) L12-9-5-1 model for $\hat{f}_{1d}$

(c) L12-4-2-1 model for $\hat{f}_{7d}$

(d) L12-4-4-1 model for $\hat{f}_{28d}$

Figure 7. Selected artificial neural network architectures.

(a) L12-10-5-1 model for $\hat{O}_m$

L12-9-5-1 model for $\hat{f}_{1d}$

L12-4-2-1 model for $\hat{f}_{7d}$

L12-4-4-1 model for $\hat{f}_{28d}$

Figure 8. RMSE versus the number of epochs for each response: (a) slump flow; (b) 1-day compressive strength; (c) 7-day compressive strength; and (d) 28-day compressive strength.

Figure 9. Regression for training (a), test (b) and all (c) for L12-10-5-1 model for $\hat{\phi}_m$.

Figure 10. Regression for training (a), test (b) and all (c) for L12-9-5-1 model for $\hat{f}_{1d}$.

Figure 11. Regression for training (a), test (b) and all (c) for L12-4-2-1 model for $\hat{f}_{7d}$.

Figure 12. Regression for training (a), test (b) and all (c) for L12-4-4-1 model for $\hat{f}_{28d}$.

3.3. Predicted slump flow and compressive strengths

The performance of the models was evaluated using the model accuracy measures tabulated in [Table 5](#).

Table 5. Models performance measures.

Data subset	Predicted feature	Model performance			
		MAE	RMSE	NMBE	R ²
Train	$\emptyset_m$ [mm]	5.448	6.397	-0.164%	0.988
	f_{1d} [MPa]	1.634	2.022	0.543%	0.977
	f_{7d} [MPa]	2.276	3.129	1.003%	0.970
	f_{28d} [MPa]	1.805	2.239	0.109%	0.982
Test	$\emptyset_m$ [mm]	5.951	7.245	-0.114%	0.982
	f_{1d} [MPa]	1.894	2.400	1.226%	0.976
	f_{7d} [MPa]	1.987	2.638	-0.230%	0.960
	f_{28d} [MPa]	1.675	2.064	-0.090%	0.983
All	$\emptyset_m$ [mm]	5.572	6.615	-0.147%	0.986
	f_{1d} [MPa]	1.685	2.113	0.733%	0.977
	f_{7d} [MPa]	2.189	3.005	0.728%	0.967
	f_{28d} [MPa]	1.760	2.189	0.062	0.982

The ANN model (L12-10-2-1) predicted the slump flow with a MAE and RMSE values of 5.951mm and 7.245 mm respectively i.e., the differences between predicted and experimental compressive strength values were small. NMBE and R² statistics of -0.114% and 0.982, respectively clearly exhibits that the predicted compressive strength values were in strong coherence with those of experimentally determined values (see [Figure 9](#)).

The ANN 1-day compressive strength predictive model (L12-9-5-1) estimated the 1-day compressive strength with a MAE and RMSE values of 1.894 MPa and 2.400 MPa, respectively. This indicates that the differences between predicted and experimentally obtained results were negligible. NMBE and R² statistics indicate a good performance of the model too. In addition, [Figure 10](#) clearly shows that the predicted 1-day compressive strength values were in strong coherence with experimental ones.

MAE, RMSE, NMBE and R² statistics for the L4-2-5-1 7-day compressive strength model of 1.987, 2.638, -0.230%, and 0.960, respectively, all of them close to the perfect-fit value threshold. The regression plot showing the prediction of trained ANN versus real 7-day compressive strength is exhibited at [Figure 11](#).

Finally, the ANN model (L4-4-1) predicted the 28-day compressive strength with a MAE value of 1.675 mm, with an RMSE of 2.064 MPa. NMBE and R² statistics of -0.090% and 0.983, respectively, showed the best performance of the model. Furthermore [Figure 12](#) clearly exhibits the strong coherence between the predicted compressive strength values and the real ones.

Those results justify that the models were able to generate the experimental results with high accuracy.

3.4. Evaluating variable importance

Artificial neural networks (ANNs) have been labeled a 'black box' because they are believed to provide little explanatory insight into the contributions of the independent variables in the prediction process. However (Olden et al., 2004) developed the Connection Weight Approach (CWA) to evaluate the importance of the variables of each model. This method calculates importance as the summed product of the raw input-hidden and hidden-output connection weights between each input and output node. An advantage is the relative contributions of each connection weight are maintained in both magnitude and sign. For example, connection weights that change sign (e.g., positive to negative) between the input-hidden to hidden-output layers would have a canceling effect (Franceschini et al., 2018). The CWA method was used in this study to evaluate the importance of every variable in each response. These analyses are of great help both to understand the influence of each of the components of the concrete on their final properties, as well as to be able to select the components that best fit the properties required in future research. The results are showed in [Figures 13–16](#).

As expected, the CWA analysis results seem to indicate that the contents of water (W) has the positive maximum importance for the slump flow prediction, followed by the superplasticizer content (PCE). Other positive factors with relative importance for the slump flow prediction were water to powder ratio (WP), recycled glass powder (GP), water to binder ratio (WB) and limestone content (LP).

The positive effect of GP could be explained because its very low water absorption (Abellán et al., 2020; Soliman & Tagnit-Hamou 2017b; Tagnit-Hamou et al., 2016b) which also improves the rheology of

Figure 13. Importance of the input variables for L12-10-5-1 model for $\hat{\theta}_m$.

Figure 14. Importance of the input variables for L12-9-5-1 model for $\hat{f}_{1d}$.

Figure 15. Importance of the input variables for L12-4-2-1 model for $\hat{f}_{7d}$.

concrete. In addition, the alkaline content of the mixture increases with the inclusion of recycled glass due to the high Na_2O content of the latter (see Table 2). Therefore, as the alkaline content increases the lower shear strength of the paste, providing the higher flow due to the higher alkalinity of the liquid phase (Abellán et al., 2020; Pedrajas et al., 2014).

Regarding to the importance of LP, Yu et al. (2014) demonstrated that using limestone powder as a cement replacement to produce UHPC can significantly improve its workability.

On the other hand, FCC has the maximum importance on the negative side (Figure 13). It could be due to the fact that the ettringite formation increases as the partial substitution of C by FCC increases (Abellán-García et al., 2019; Arizzi & Cultrone, 2018; Torres Castellanos, 2014) which decreases the flow ability of the concrete. Moreover, several studies have demonstrated that the inclusion of FCC in concrete

Figure 16. Importance of the input variables for L12-4-4-1 model for $\hat{f}_{28d}$.

requires more water to reach a determined workability (Abellán-García et al., 2019; Arizzi & Cultrone, 2018; Camacho Torregrosa, 2013; Torres Castellanos, 2014).

Figures 14–16 showed the CWA for 1-day, 7-day and 28-day compressive strength. In all those plots, it can be appreciated that the most importance inputs belong to Cement, Virtual Packing Density and Silica Fume content. This would agree with the studies that justify the ultra-high compressive strength of UHPC due to its ultra-dense structure (Abbas et al., 2016; Ghafari et al., 2014; Schmidt & Schmidt, 2012). It is also important to denote that, because of its lower size ($d_{50} = 0.15 \mu\text{m}$), silica fume content is closely related to VPD because it fills the gap between the other particles.

Regarding compressive strength, polycarboxylate content has a negative effect for the early-strength but a positive effect on the 28-day compressive strength (Figures 14–16). This negative effect of polycarboxylate on early strength development has been demonstrated by several researchers (Abellan et al., 2018a; Abellán et al., 2020; Kubens, 2010; Puertas et al., 2005). The polycarboxylate-based ether superplasticizer slows down the hydration of silicates (especially the alite phase) and affects the formation of ettringite (Puertas et al., 2005).

It can be noticed that FCC has a relevant and positive importance in the 1-day compressive strength that disappears over that age. This may be due to the reported high reactivity of FCC at early age (Torres Castellanos, 2014; Torres Castellanos & Torres Agredo, 2010). However, those studies have also shown that over that age, it possibly leads to the release of heat, probably because of smaller amounts of calcium silicate hydrate (CSH) phase being formed.

4. Conclusions

This study provides four accuracy ANN models to predict the 1-day, 7-day, and 28-day compressive strengths and slump flow of UHPC using different combinations of supplementary cementitious materials, such as silica fume, FCC, micro limestone powder, limestone powder, recycled glass powder, recycled glass flour and quartz powder. To avoid overfitting, K-Fold validation with four partitions was used. In future research these mathematical models could help reduce the number of tests required in the development of new UHPC-type materials, decreasing both time and costs associated with the experimental campaign.

The architectures selected for models for predicted 1-day, 7-day, and 28-day compressive strengths and slump flow were L12-9-2-1, L12-5-2-1, L12-4-4-1, and L12-10-5-1, and their best performance was obtained at epoch 161, 144, 137, and 156 respectively. Besides, the ANN models predicted the 1-day, 7-day, and 28-day compressive strengths and slump flow of the test set with prediction error values of 2.400 MPa, 2.638 MPa, 2.064 MPa and 7.245 mm respectively, i.e. very close to real values. In general, it was observed that the prediction done using ANN shows a strong degree of coherency with experimentally determined slump flow and 1-day, 7-day, and 28-day compressive strengths of UHPC with R^2 values of 0.982, 0.976, 0.960, and 0.983, respectively.

The inclusion of input variables such as the water to binder ratio, water to total powders ratio and virtual packing density contributed substantially to the accuracy of predicting the properties of UHPC incorporating supplementary cementitious materials. However, the yield of the models could be enhanced by

taking into account more variables such as additional physical and chemical properties of cement, supplementary cementitious materials and sand in a future research.

In addition, the importance of the input variables was analyzed through CWA methodology, demonstrating that the most positive factors in all ages of compressive strength are C, SF and VPD, whilst the negative are water content and water to binder ratio. CWA analysis also showed that polycarboxylate content had a negative effect for the early-strength but a positive effect on the 28-day compressive strength. Besides, the inclusion of FCC improves the 1-day compressive strength, although it substantially reduces the slump flow of concrete. Furthermore, the most positive factors in slump flow are W, PCE and WP. On the other hand, the most negative factors for rheology are FCC, SS and VPD. The analysis also indicated that the inclusion of GP, and to a lesser extent of LP, in the mixture improves the flowability of UHPC, allowing a reduction of the necessary amount of plasticizer to achieve the desired rheology, thus reducing the total cost of concrete.

Areas for future research include the analysis and development of neural networks regression models for other properties of UHPC such as module of elasticity, chloride penetration, shrinkage, and carbonization, even for the properties derived from the addition of fibers to the UHPC such as toughness and ductility.

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Appendix A

Proportion of mix components expressed as a function of the weight of cement.

N	C	SF	GP	FCC	LP	QP	SS	PCE	W	W/B	W/P	VPD
1	1	0.150	0.000	0.000	0.000	0.000	1.926	0.030	0.282	0.245	0.245	0.818
2	1	0.150	0.000	0.000	0.000	0.000	1.399	0.025	0.236	0.205	0.205	0.791
3	1	0.150	0.000	0.000	0.000	0.000	1.037	0.025	0.201	0.175	0.175	0.766
4	1	0.150	0.000	0.000	0.000	0.000	1.037	0.030	0.191	0.166	0.166	0.766
5	1	0.150	0.000	0.000	0.000	0.000	1.057	0.030	0.186	0.162	0.162	0.767
6	1	0.000	0.000	0.103	0.000	0.000	1.982	0.031	0.297	0.270	0.270	0.766
7	1	0.000	0.000	0.103	0.000	0.000	1.480	0.031	0.231	0.210	0.210	0.737
8	1	0.000	0.000	0.155	0.000	0.000	0.939	0.046	0.230	0.200	0.200	0.692
9	1	0.000	0.000	0.155	0.000	0.000	0.963	0.046	0.219	0.190	0.190	0.686
10	1	0.000	0.000	0.155	0.000	0.000	0.988	0.046	0.213	0.185	0.185	0.688
11	1	0.000	0.000	0.155	0.000	0.000	0.988	0.046	0.207	0.180	0.180	0.688
12	1	0.150	0.000	0.000	0.000	0.000	0.865	0.046	0.242	0.210	0.210	0.753
13	1	0.150	0.000	0.000	0.000	0.000	0.914	0.046	0.224	0.195	0.195	0.757
14	1	0.100	0.000	0.000	0.000	0.000	1.968	0.031	0.297	0.270	0.270	0.798
15	1	0.000	0.000	0.103	0.000	0.000	1.982	0.031	0.297	0.270	0.270	0.766
16	1	0.100	0.000	0.000	0.000	0.000	1.457	0.031	0.231	0.210	0.210	0.771
17	1	0.000	0.000	0.103	0.000	0.000	1.486	0.031	0.231	0.210	0.210	0.737
18	1	0.100	0.000	0.000	0.000	0.000	1.410	0.046	0.242	0.220	0.220	0.775
19	1	0.000	0.000	0.103	0.000	0.000	1.457	0.046	0.231	0.210	0.210	0.733
20	1	0.150	0.000	0.000	0.000	0.000	0.890	0.035	0.242	0.210	0.210	0.755
21	1	0.000	0.000	0.155	0.000	0.000	0.963	0.035	0.230	0.200	0.200	0.686
22	1	0.150	0.000	0.000	0.000	0.000	0.914	0.046	0.224	0.195	0.195	0.757
23	1	0.000	0.000	0.155	0.000	0.000	0.963	0.046	0.219	0.190	0.190	0.686
24	1	0.000	0.000	0.155	0.000	0.000	1.062	0.030	0.201	0.175	0.175	0.695
25	1	0.150	0.000	0.000	0.000	0.000	1.037	0.025	0.201	0.175	0.175	0.766
26	1	0.250	0.000	0.000	0.000	0.000	1.332	0.046	0.275	0.220	0.220	0.825
27	1	0.250	0.000	0.000	0.000	0.000	1.424	0.025	0.256	0.205	0.205	0.827
28	1	0.000	0.000	0.258	0.000	0.000	1.486	0.025	0.256	0.205	0.205	0.723
29	1	0.100	0.000	0.000	0.000	0.000	1.911	0.046	0.308	0.280	0.280	0.803
30	1	0.100	0.000	0.000	0.000	0.000	3.015	0.046	0.363	0.330	0.330	0.809
31	1	0.100	0.000	0.000	0.000	0.000	2.958	0.046	0.396	0.360	0.360	0.802
32	1	0.000	0.000	0.103	0.000	0.000	1.457	0.025	0.253	0.230	0.230	0.735
33	1	0.000	0.000	0.103	0.000	0.000	2.462	0.025	0.275	0.250	0.250	0.791
34	1	0.100	0.000	0.000	0.000	0.000	1.399	0.030	0.253	0.230	0.230	0.767
35	1	0.100	0.000	0.000	0.000	0.000	2.415	0.030	0.275	0.250	0.250	0.783
36	1	0.000	0.000	0.103	0.000	0.000	1.369	0.046	0.264	0.240	0.240	0.727
37	1	0.000	0.000	0.103	0.000	0.000	2.330	0.046	0.297	0.270	0.270	0.772
38	1	0.100	0.000	0.000	0.000	0.000	1.399	0.046	0.242	0.220	0.220	0.774
39	1	0.100	0.000	0.000	0.000	0.000	2.353	0.046	0.286	0.260	0.260	0.774
40	1	0.000	0.000	0.155	0.000	0.000	0.973	0.046	0.219	0.190	0.190	0.687
41	1	0.000	0.000	0.155	0.000	0.000	1.786	0.046	0.253	0.220	0.220	0.725
42	1	0.100	0.000	0.000	0.000	0.000	1.911	0.046	0.308	0.280	0.280	0.803
43	1	0.100	0.000	0.000	0.000	0.000	1.798	0.046	0.341	0.310	0.310	0.798
44	1	0.000	0.000	0.103	0.000	0.000	1.486	0.030	0.231	0.210	0.210	0.737
45	1	0.000	0.000	0.103	0.000	0.000	1.428	0.030	0.253	0.230	0.230	0.733
46	1	0.100	0.000	0.000	0.000	0.000	1.457	0.030	0.231	0.210	0.210	0.771
47	1	0.100	0.000	0.000	0.000	0.000	1.399	0.030	0.253	0.230	0.230	0.768
48	1	0.000	0.000	0.103	0.000	0.000	1.457	0.046	0.231	0.210	0.210	0.733
49	1	0.000	0.000	0.103	0.000	0.000	1.399	0.046	0.253	0.230	0.230	0.729
50	1	0.150	0.000	0.000	0.000	0.000	1.013	0.026	0.213	0.185	0.185	0.760
51	1	0.150	0.000	0.000	0.000	0.000	1.019	0.026	0.201	0.175	0.175	0.760
52	1	0.100	0.000	0.000	0.000	0.000	2.014	0.033	0.292	0.265	0.265	0.798
53	1	0.150	0.000	0.000	0.000	0.000	1.423	0.034	0.242	0.210	0.210	0.786
54	1	0.000	0.000	0.155	0.000	0.000	1.056	0.034	0.201	0.175	0.175	0.695
55	1	0.150	0.000	0.000	0.000	0.200	1.225	0.040	0.236	0.175	0.165	0.775
56	1	0.000	0.000	0.154	0.000	0.000	1.674	0.034	0.241	0.210	0.210	0.747
57	1	0.110	0.000	0.000	0.000	0.000	1.057	0.012	0.167	0.150	0.150	0.745
58	1	0.130	0.182	0.000	0.000	0.000	1.204	0.014	0.197	0.150	0.150	0.740
59	1	0.158	0.443	0.000	0.000	0.000	1.415	0.017	0.239	0.150	0.150	0.734
60	1	0.250	0.000	0.000	0.000	0.299	1.129	0.015	0.310	0.248	0.200	0.775
61	1	0.251	0.000	0.000	0.000	0.273	1.037	0.013	0.283	0.226	0.186	0.772
62	1	0.000	0.000	0.000	0.000	0.000	0.964	0.013	0.180	0.180	0.180	0.829
63	1	0.288	0.000	0.000	0.000	0.000	1.089	0.055	0.232	0.180	0.180	0.817
64	1	0.000	0.000	0.000	0.000	0.000	3.093	0.031	0.322	0.322	0.322	0.829

(continued)

Continued.

N	C	SF	GP	FCC	LP	QP	SS	PCE	W	W/B	W/P	VPD
65	1	0.324	0.000	0.000	0.000	0.432	1.409	0.095	0.272	0.205	0.155	0.793
66	1	0.333	0.000	0.000	0.000	0.433	1.416	0.065	0.329	0.247	0.186	0.795
67	1	0.500	0.000	0.000	0.000	0.396	1.345	0.348	0.097	0.065	0.051	0.825
68	1	0.100	0.000	0.000	0.000	0.000	2.393	0.046	0.260	0.236	0.236	0.780
69	1	0.000	0.000	0.103	0.000	0.000	1.515	0.046	0.210	0.191	0.191	0.738
70	1	0.000	0.000	0.155	0.000	0.000	1.125	0.031	0.175	0.152	0.152	0.702
71	1	0.000	0.000	0.000	0.000	0.000	3.745	0.020	0.300	0.300	0.300	0.849
72	1	0.000	0.000	0.000	0.000	0.000	3.745	0.020	0.300	0.300	0.300	0.849
73	1	0.000	0.000	0.000	0.000	0.000	3.745	0.020	0.300	0.300	0.300	0.849
74	1	0.200	0.000	0.000	0.000	0.000	0.000	0.012	0.200	0.167	0.167	0.670
75	1	0.300	0.000	0.000	0.000	0.000	0.000	0.013	0.200	0.154	0.154	0.733
76	1	0.200	0.000	0.000	0.000	0.000	1.577	0.012	0.240	0.200	0.200	0.824
77	1	0.000	0.000	0.000	0.000	0.000	1.264	0.013	0.226	0.226	0.226	0.837
78	1	0.100	0.000	0.000	0.000	0.000	1.392	0.014	0.248	0.225	0.225	0.784
79	1	0.200	0.000	0.000	0.000	0.000	1.518	0.015	0.270	0.225	0.225	0.825
80	1	0.300	0.000	0.000	0.000	0.000	1.645	0.017	0.293	0.225	0.225	0.861
81	1	0.100	0.000	0.000	0.000	0.137	1.251	0.014	0.247	0.225	0.200	0.791
82	1	0.100	0.000	0.000	0.000	0.275	1.114	0.014	0.247	0.225	0.180	0.798
83	1	0.100	0.000	0.000	0.000	0.413	0.974	0.014	0.247	0.225	0.163	0.805
84	1	0.100	0.000	0.000	0.000	0.275	1.114	0.014	0.247	0.225	0.180	0.734
85	1	0.000	0.000	0.000	0.000	0.000	1.264	0.024	0.200	0.200	0.200	0.856
86	1	0.000	0.000	0.000	0.000	0.000	1.292	0.024	0.200	0.200	0.200	0.856
87	1	0.000	0.000	0.000	0.000	0.000	1.319	0.024	0.200	0.200	0.200	0.856
88	1	0.000	0.000	0.000	0.000	0.000	1.292	0.024	0.200	0.200	0.200	0.856
89	1	0.000	0.000	0.000	0.000	0.000	1.319	0.024	0.200	0.200	0.200	0.856
90	1	0.000	0.000	0.000	0.000	0.000	1.265	0.010	0.200	0.200	0.200	0.856
91	1	0.200	0.000	0.000	0.000	0.000	1.518	0.012	0.241	0.200	0.200	0.825
92	1	0.199	0.000	0.000	0.000	0.000	1.583	0.012	0.240	0.200	0.200	0.824
93	1	0.200	0.000	0.000	0.000	0.000	1.583	0.012	0.240	0.200	0.200	0.824
94	1	0.000	0.000	0.000	0.000	0.000	0.506	0.012	0.222	0.202	0.202	0.653
95	1	0.000	0.000	0.000	0.000	0.000	1.265	0.012	0.214	0.204	0.204	0.746
96	1	0.000	0.000	0.000	0.000	0.000	0.506	0.018	0.222	0.202	0.202	0.653
97	1	0.000	0.000	0.000	0.000	0.000	1.265	0.018	0.214	0.204	0.204	0.746
98	1	0.000	0.000	0.000	0.000	0.000	1.619	0.018	0.215	0.205	0.205	0.774
99	1	0.000	0.000	0.000	0.000	0.000	0.506	0.024	0.222	0.202	0.202	0.653
100	1	0.000	0.000	0.000	0.000	0.000	1.265	0.024	0.214	0.204	0.204	0.746
101	1	0.000	0.000	0.000	0.000	0.000	1.619	0.024	0.215	0.205	0.205	0.774
102	1	0.000	0.000	0.000	0.000	0.000	2.022	0.024	0.217	0.206	0.206	0.746
103	1	0.000	0.000	0.000	0.000	0.000	0.506	0.036	0.212	0.202	0.202	0.653
104	1	0.000	0.000	0.000	0.000	0.000	1.265	0.036	0.214	0.204	0.204	0.746
105	1	0.000	0.000	0.000	0.000	0.000	1.619	0.036	0.215	0.205	0.205	0.774
106	1	0.000	0.000	0.000	0.000	0.000	2.022	0.036	0.217	0.206	0.206	0.746
107	1	0.100	0.000	0.000	0.000	0.000	0.556	0.020	0.222	0.202	0.202	0.704
108	1	0.100	0.000	0.000	0.000	0.000	1.392	0.020	0.225	0.204	0.204	0.784
109	1	0.100	0.000	0.000	0.000	0.000	1.780	0.020	0.225	0.205	0.205	0.806
110	1	0.099	0.000	0.000	0.000	0.000	2.224	0.020	0.227	0.206	0.206	0.757
111	1	0.100	0.000	0.000	0.000	0.000	0.556	0.026	0.222	0.202	0.202	0.704
112	1	0.100	0.000	0.000	0.000	0.000	1.392	0.026	0.225	0.204	0.204	0.784
113	1	0.100	0.000	0.000	0.000	0.000	1.780	0.026	0.225	0.205	0.205	0.806
114	1	0.099	0.000	0.000	0.000	0.000	2.224	0.026	0.227	0.206	0.206	0.757
115	1	0.200	0.000	0.000	0.000	0.000	1.020	0.021	0.240	0.200	0.200	0.670
116	1	0.200	0.000	0.000	0.000	0.000	0.607	0.021	0.242	0.202	0.202	0.757
117	1	0.200	0.000	0.000	0.000	0.000	1.517	0.021	0.245	0.204	0.204	0.824
118	1	0.200	0.000	0.000	0.000	0.000	1.943	0.021	0.246	0.205	0.205	0.818
119	1	0.200	0.000	0.000	0.000	0.000	2.427	0.022	0.246	0.205	0.205	0.766
120	1	0.200	0.000	0.000	0.000	0.000	1.560	0.029	0.240	0.200	0.200	0.670
121	1	0.200	0.000	0.000	0.000	0.000	0.607	0.029	0.242	0.202	0.202	0.757
122	1	0.200	0.000	0.000	0.000	0.000	1.517	0.028	0.252	0.210	0.210	0.824
123	1	0.200	0.000	0.000	0.000	0.000	1.943	0.029	0.246	0.205	0.205	0.818
124	1	0.200	0.000	0.000	0.000	0.000	2.427	0.029	0.246	0.205	0.205	0.766
125	1	0.200	0.000	0.000	0.000	0.000	0.000	0.029	0.240	0.200	0.200	0.670
126	1	0.300	0.000	0.000	0.000	0.000	0.000	0.031	0.260	0.200	0.200	0.733
127	1	0.000	0.000	0.000	0.000	0.000	0.506	0.024	0.200	0.200	0.200	0.701
128	1	0.000	0.000	0.000	0.000	0.000	1.265	0.024	0.200	0.200	0.200	0.810

(continued)

Continued.

N	C	SF	GP	FCC	LP	QP	SS	PCE	W	W/B	W/P	VPD
129	1	0.000	0.000	0.000	0.000	0.000	1.619	0.024	0.200	0.200	0.200	0.794
130	1	0.000	0.000	0.000	0.000	0.000	1.292	0.024	0.200	0.200	0.200	0.810
131	1	0.000	0.000	0.000	0.000	0.000	1.649	0.024	0.200	0.200	0.200	0.794
132	1	0.000	0.000	0.000	0.000	0.000	1.318	0.024	0.200	0.200	0.200	0.810
133	1	0.000	0.000	0.000	0.000	0.000	1.680	0.024	0.200	0.200	0.200	0.794
134	1	0.000	0.000	0.000	0.000	0.000	1.345	0.024	0.200	0.200	0.200	0.810
135	1	0.000	0.000	0.000	0.000	0.000	1.710	0.024	0.200	0.200	0.200	0.795
136	1	0.200	0.000	0.000	0.000	0.000	0.000	0.024	0.200	0.167	0.167	0.670
137	1	0.300	0.000	0.000	0.000	0.000	0.000	0.024	0.200	0.154	0.154	0.733
138	1	0.200	0.000	0.000	0.000	0.000	1.324	0.024	0.200	0.167	0.167	0.810
139	1	0.200	0.000	0.000	0.000	0.000	1.685	0.024	0.200	0.167	0.167	0.830
140	1	0.300	0.000	0.000	0.000	0.000	1.327	0.024	0.200	0.154	0.154	0.845
141	1	0.200	0.000	0.000	0.000	0.000	0.000	0.029	0.240	0.200	0.200	0.670
142	1	0.200	0.000	0.000	0.000	0.000	0.000	0.029	0.216	0.180	0.180	0.670
143	1	0.200	0.000	0.000	0.000	0.000	0.000	0.029	0.213	0.177	0.177	0.670
144	1	0.200	0.000	0.000	0.000	0.000	0.000	0.029	0.236	0.197	0.197	0.670
145	1	0.249	0.000	0.000	0.000	0.000	1.307	0.025	0.204	0.164	0.164	0.831
146	1	0.257	0.000	0.000	0.000	0.000	1.315	0.026	0.206	0.164	0.164	0.835
147	1	0.265	0.000	0.000	0.000	0.000	1.324	0.026	0.207	0.164	0.164	0.838
148	1	0.273	0.000	0.000	0.000	0.000	1.332	0.026	0.208	0.164	0.164	0.842
149	1	0.281	0.000	0.000	0.000	0.000	1.340	0.026	0.210	0.164	0.164	0.845
150	1	0.284	0.000	0.000	0.000	0.298	1.205	0.040	0.248	0.212	0.154	0.789
151	1	0.283	0.000	0.000	0.000	0.297	1.223	0.041	0.247	0.188	0.153	0.610
152	1	0.284	0.000	0.000	0.000	0.297	1.247	0.041	0.246	0.212	0.153	0.793
153	1	0.283	0.000	0.000	0.000	0.000	1.199	0.016	0.247	0.212	0.212	0.790
154	1	0.000	0.278	0.000	0.000	0.000	1.199	0.016	0.246	0.212	0.212	0.690
155	1	0.000	0.278	0.000	0.000	0.000	1.199	0.016	0.246	0.212	0.153	0.710
156	1	0.000	0.278	0.000	0.000	0.000	1.199	0.016	0.246	0.212	0.153	0.730
157	1	0.000	0.278	0.000	0.000	0.000	1.199	0.016	0.246	0.212	0.153	0.740
158	1	0.204	0.077	0.000	0.000	0.000	1.201	0.016	0.248	0.212	0.154	0.780
159	1	0.141	0.138	0.000	0.000	0.000	1.201	0.016	0.246	0.212	0.153	0.770
160	1	0.085	0.194	0.000	0.000	0.000	1.200	0.016	0.246	0.212	0.153	0.750
161	1	0.000	0.278	0.000	0.000	0.000	1.199	0.016	0.246	0.212	0.153	0.730
162	1	0.200	0.000	0.000	0.000	0.000	0.000	0.012	0.240	0.200	0.200	0.670
163	1	0.300	0.000	0.000	0.000	0.000	0.000	0.013	0.260	0.200	0.200	0.733
164	1	0.200	0.000	0.000	0.000	0.000	1.599	0.012	0.240	0.200	0.200	0.824
165	1	0.400	0.000	0.000	0.000	0.100	1.294	0.029	0.216	0.164	0.153	0.827
166	1	0.277	0.000	0.000	0.499	0.000	1.174	0.029	0.304	0.172	0.172	0.777
167	1	0.262	0.000	0.000	0.418	0.000	1.093	0.035	0.290	0.173	0.173	0.773
168	1	0.277	0.000	0.000	0.494	0.000	1.160	0.029	0.312	0.177	0.177	0.777
169	1	0.304	0.000	0.000	0.417	0.000	1.029	0.079	0.252	0.147	0.147	0.783
170	1	0.304	0.000	0.000	0.417	0.000	1.020	0.042	0.290	0.169	0.169	0.783
171	1	0.277	0.000	0.000	0.499	0.000	1.239	0.030	0.292	0.165	0.165	0.781
172	1	0.304	0.000	0.000	0.417	0.000	1.097	0.035	0.267	0.156	0.156	0.787
173	1	0.200	0.000	0.000	0.000	0.000	0.856	0.030	0.219	0.183	0.183	0.765
174	1	0.200	0.000	0.000	0.000	0.000	0.855	0.030	0.199	0.166	0.166	0.765
175	1	0.200	0.000	0.000	0.000	0.000	0.856	0.030	0.219	0.183	0.183	0.765
176	1	0.200	0.000	0.000	0.000	0.000	0.855	0.030	0.199	0.166	0.166	0.765
177	1	0.200	0.000	0.000	0.000	0.000	0.855	0.030	0.209	0.174	0.174	0.765
178	1	0.200	0.000	0.000	0.000	0.000	0.856	0.030	0.229	0.191	0.191	0.765
179	1	0.200	0.000	0.000	0.000	0.000	0.855	0.030	0.209	0.174	0.174	0.765
180	1	0.200	0.000	0.000	0.000	0.000	0.855	0.030	0.209	0.174	0.174	0.765
181	1	0.284	0.000	0.000	0.425	0.000	1.111	0.029	0.291	0.171	0.171	0.781
182	1	0.266	0.000	0.000	0.415	0.000	1.187	0.029	0.273	0.163	0.163	0.780
183	1	0.253	0.000	0.000	0.415	0.000	1.202	0.029	0.273	0.164	0.164	0.777
184	1	0.253	0.000	0.000	0.415	0.000	1.203	0.028	0.273	0.165	0.165	0.777
185	1	0.26	0.000	0.000	0.415	0.000	1.056	0.011	0.326	0.195	0.195	0.771
186	1	0.260	0.000	0.000	0.415	0.000	1.186	0.011	0.277	0.166	0.166	0.778
187	1	0.260	0.000	0.000	0.415	0.000	1.113	0.011	0.305	0.183	0.183	0.774
188	1	0.260	0.000	0.000	0.415	0.000	1.105	0.014	0.305	0.182	0.182	0.774
189	1	0.260	0.000	0.000	0.415	0.000	1.112	0.011	0.305	0.183	0.183	0.774
190	1	0.260	0.000	0.000	0.415	0.000	1.105	0.013	0.305	0.183	0.183	0.774
191	1	0.260	0.000	0.000	0.415	0.000	1.105	0.013	0.305	0.183	0.183	0.774
192	1	0.260	0.000	0.000	0.415	0.000	1.082	0.023	0.305	0.183	0.183	0.773

(continued)

Continued.

N	C	SF	GP	FCC	LP	QP	SS	PCE	W	W/B	W/P	VPD
193	1	0.260	0.000	0.000	0.415	0.000	1.082	0.023	0.305	0.183	0.183	0.773
194	1	0.260	0.000	0.000	0.415	0.000	1.082	0.023	0.305	0.183	0.183	0.773
195	1	0.328	0.000	0.000	0.539	0.000	1.600	0.033	0.350	0.188	0.188	0.787
196	1	0.328	0.000	0.000	0.539	0.000	1.600	0.048	0.302	0.162	0.162	0.787
197	1	0.328	0.000	0.000	0.539	0.000	1.600	0.049	0.338	0.182	0.182	0.787
198	1	0.328	0.000	0.000	0.539	0.000	1.600	0.032	0.313	0.168	0.168	0.787
199	1	0.274	0.000	0.054	0.539	0.000	1.600	0.033	0.350	0.188	0.188	0.625
200	1	0.274	0.000	0.054	0.539	0.000	1.600	0.048	0.302	0.162	0.162	0.625
201	1	0.274	0.000	0.054	0.539	0.000	1.600	0.049	0.338	0.182	0.182	0.625
202	1	0.274	0.000	0.054	0.539	0.000	1.600	0.032	0.313	0.168	0.168	0.625
203	1	0.219	0.000	0.107	0.539	0.000	1.600	0.032	0.350	0.188	0.188	0.634
204	1	0.219	0.000	0.107	0.539	0.000	1.600	0.048	0.302	0.162	0.162	0.634
205	1	0.219	0.000	0.107	0.539	0.000	1.600	0.049	0.339	0.182	0.182	0.634
206	1	0.219	0.000	0.107	0.539	0.000	1.600	0.032	0.313	0.168	0.168	0.634
207	1	0.163	0.000	0.163	0.539	0.000	1.600	0.032	0.350	0.188	0.188	0.643
208	1	0.169	0.552	0.000	0.391	0.000	1.495	0.036	0.312	0.148	0.148	0.766
209	1	0.163	0.000	0.163	0.539	0.000	1.600	0.048	0.302	0.162	0.162	0.643
210	1	0.163	0.000	0.163	0.539	0.000	1.600	0.049	0.339	0.182	0.182	0.643
211	1	0.163	0.000	0.163	0.539	0.000	1.600	0.032	0.313	0.168	0.168	0.643
212	1	0.169	0.268	0.083	0.407	0.000	1.771	0.036	0.283	0.147	0.147	0.687
213	1	0.154	0.164	0.076	0.362	0.000	1.617	0.033	0.258	0.147	0.147	0.703
214	1	0.169	0.268	0.083	0.407	0.000	1.720	0.036	0.302	0.157	0.157	0.689
215	1	0.154	0.164	0.076	0.362	0.000	1.571	0.033	0.275	0.157	0.157	0.706
216	1	0.169	0.268	0.083	0.407	0.000	1.767	0.044	0.278	0.144	0.144	0.687
217	1	0.154	0.164	0.076	0.362	0.000	1.613	0.040	0.253	0.144	0.144	0.703
218	1	0.169	0.268	0.083	0.407	0.000	1.716	0.044	0.297	0.154	0.154	0.689
219	1	0.154	0.164	0.076	0.362	0.000	1.567	0.040	0.271	0.154	0.154	0.706
220	1	0.161	0.214	0.079	0.384	0.000	1.664	0.038	0.276	0.150	0.150	0.696
221	1	0.161	0.214	0.079	0.384	0.000	1.664	0.038	0.276	0.150	0.150	0.696
222	1	0.177	0.313	0.087	0.422	0.000	1.800	0.042	0.300	0.150	0.150	0.683
223	1	0.148	0.133	0.073	0.349	0.000	1.529	0.035	0.256	0.151	0.151	0.712
224	1	0.161	0.214	0.079	0.384	0.000	1.708	0.038	0.260	0.142	0.142	0.694
225	1	0.161	0.214	0.079	0.384	0.000	1.620	0.038	0.293	0.159	0.159	0.699
226	1	0.161	0.214	0.079	0.384	0.000	1.668	0.032	0.281	0.153	0.153	0.696
227	1	0.161	0.214	0.079	0.384	0.000	1.660	0.044	0.272	0.148	0.148	0.696
228	1	0.161	0.214	0.079	0.384	0.000	1.664	0.038	0.276	0.150	0.150	0.696
229	1	0.161	0.214	0.079	0.384	0.000	1.664	0.038	0.276	0.150	0.150	0.696
230	1	0.167	0.625	0.000	0.226	0.000	1.552	0.036	0.294	0.146	0.146	0.726
231	1	0.154	0.492	0.000	0.173	0.000	1.510	0.033	0.264	0.145	0.145	0.732
232	1	0.167	0.625	0.000	0.226	0.000	1.499	0.036	0.314	0.155	0.155	0.730
233	1	0.154	0.492	0.000	0.173	0.000	1.463	0.033	0.282	0.155	0.155	0.736
234	1	0.167	0.625	0.000	0.226	0.000	1.548	0.043	0.289	0.143	0.143	0.726
235	1	0.154	0.492	0.000	0.173	0.000	1.506	0.040	0.259	0.142	0.142	0.732
236	1	0.167	0.625	0.000	0.183	0.000	1.553	0.043	0.302	0.153	0.153	0.729
237	1	0.154	0.492	0.000	0.136	0.000	1.459	0.040	0.290	0.163	0.163	0.739
238	1	0.160	0.540	0.000	0.191	0.000	1.539	0.038	0.281	0.149	0.149	0.729
239	1	0.160	0.540	0.000	0.191	0.000	1.539	0.038	0.281	0.149	0.149	0.729
240	1	0.172	0.646	0.000	0.232	0.000	1.625	0.041	0.304	0.149	0.149	0.721
241	1	0.149	0.449	0.000	0.162	0.000	1.434	0.035	0.269	0.153	0.153	0.739
242	1	0.160	0.540	0.000	0.191	0.000	1.583	0.038	0.264	0.140	0.140	0.726
243	1	0.160	0.540	0.000	0.191	0.000	1.495	0.038	0.298	0.158	0.158	0.732
244	1	0.160	0.540	0.000	0.191	0.000	1.543	0.032	0.285	0.151	0.151	0.728
245	1	0.160	0.540	0.000	0.191	0.000	1.535	0.044	0.277	0.146	0.146	0.729
246	1	0.160	0.540	0.000	0.191	0.000	1.539	0.038	0.281	0.149	0.149	0.729
247	1	0.160	0.540	0.000	0.165	0.000	1.539	0.038	0.281	0.151	0.151	0.730
248	1	0.169	0.552	0.000	0.391	0.000	1.495	0.036	0.312	0.148	0.148	0.766
249	1	0.154	0.452	0.000	0.310	0.000	1.373	0.033	0.283	0.148	0.148	0.776
250	1	0.169	0.552	0.000	0.391	0.000	1.439	0.036	0.333	0.158	0.158	0.771
251	1	0.154	0.452	0.000	0.310	0.000	1.323	0.033	0.302	0.158	0.158	0.782
252	1	0.169	0.552	0.000	0.391	0.000	1.491	0.044	0.307	0.146	0.146	0.766
253	1	0.154	0.452	0.000	0.310	0.000	1.369	0.040	0.279	0.145	0.145	0.777
254	1	0.169	0.552	0.000	0.391	0.000	1.435	0.044	0.328	0.156	0.156	0.771
255	1	0.154	0.452	0.000	0.310	0.000	1.319	0.040	0.298	0.155	0.155	0.782
256	1	0.161	0.512	0.000	0.359	0.000	1.370	0.038	0.308	0.152	0.152	0.777

(continued)

Continued.

N	C	SF	GP	FCC	LP	QP	SS	PCE	W	W/B	W/P	VPD
257	1	0.161	0.512	0.000	0.359	0.000	1.370	0.038	0.308	0.152	0.152	0.777
258	1	0.177	0.599	0.000	0.430	0.000	1.513	0.042	0.334	0.152	0.152	0.765
259	1	0.148	0.416	0.000	0.280	0.000	1.310	0.035	0.280	0.152	0.152	0.783
260	1	0.161	0.512	0.000	0.359	0.000	1.418	0.038	0.290	0.143	0.143	0.773
261	1	0.161	0.512	0.000	0.359	0.000	1.322	0.038	0.327	0.161	0.161	0.782
262	1	0.161	0.512	0.000	0.359	0.000	1.374	0.032	0.313	0.154	0.154	0.777
263	1	0.161	0.512	0.000	0.359	0.000	1.366	0.044	0.304	0.150	0.150	0.778
264	1	0.161	0.512	0.000	0.359	0.000	1.370	0.038	0.308	0.152	0.152	0.777
265	1	0.161	0.512	0.000	0.359	0.000	1.370	0.038	0.308	0.152	0.152	0.777