2024 Scienceline Publication

Journal of Civil Engineering and Urbanism

Volume 14, Issue 4: 356-367; December 25, 2024 ISSN-2252-0430

DOI: https://dx.doi.org/10.54203/jceu.2024.40

Prediction of Compressive Strength and Design Parameters of C30/37, C35/45 and C40/50 Concrete Classes by ANN

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RESEARCH ARTICLE
PII: S225204302400040-14
Received: October 01, 2024
Revised: December 20, 2024
Accepted: December 22, 2024

ABSTRACT

The quality of concrete used in the construction sector is increasing day by day with ready-mixed concrete production. The quality of concrete is directly related to its compressive strength and the related tests are labor-intensive and time-consuming. Therefore, different artificial intelligence-based models are used to predict the compressive strength of concrete. In this study, compressive strength and design parameters of concrete classes C30/37, C35/45 and C40/50 were predicted by ANN model. A total of 240 compressive strength results obtained from concretes produced in a ready-mixed concrete plant for the construction of columns, beams, decks and stairs. 70% of these data were used for training and remaining 30% of data were reserved for testing. The prediction accuracy of the ANN model was evaluated by R^2, MAPE and RMSE statistical methods. According to results, the compressive strengths of concrete classes C30/37, C35/45 and C40/50 could be predicted with errors of -0.70%, 1.25% and 0.17% for 7 days and 0.99%, 0.03% and -0.69% for 28 days, respectively. Depending on the design parameters, it was found that prediction performance could be made with almost 100% accuracy for all concretes except high-performance superplasticizer admixture. As a result, it was concluded that 'very good' or 'high accuracy' predictions can be made with ANN models.

Keywords: ANN, Compressive Strength, Concrete, Design Parameters.

INTRODUCTION

Concrete is one of the most commonly used building materials in the construction industry and stands out as a material that has been extensively researched in terms of both strength and durability properties (Yurt and Emiroğlu, 2018; Yurt and Emiroğlu, 2024). The quality of concrete used in the construction industry has changed significantly with the increase in ready-mixed concrete production. Ready-mixed concrete is produced by mixing the materials (cement, aggregate, water, and/or chemical and mineral additives) that are brought together in appropriate proportions with computer control in a concrete plant or mixer and delivered to the consumer as "fresh concrete" (Ünal and Yurtcu, 2007). Thanks to ready-mixed concrete technology, both the mass production of the required concrete and its desired properties have been achieved. Therefore, today, the production and use of concretes with compressive strength of C30/37 or higher have become widespread (Dündar et al., 2017). Compressive strength is directly related to the safety of structures constructed from concrete and must comply with relevant standard codes that vary between countries. To determine the compressive strengths of concrete, cylindrical or cubic samples are tested using a pressure testing machine after the required curing period. The 28-day compressive strength of the resulting cylindrical or cube specimens is accepted as the characteristic compressive strength of concrete by national and international regulations. These tests are labor intensive and time consuming. Therefore, different methods such as artificial intelligence-based models, regression methods and numerical simulation are used to predict the compressive strength of concrete. However, the complex non-linear correlation between the variables involved makes it very difficult to obtain accurate values of compressive strength (Chou et al., 2022).

In this context, artificial neural networks (ANN), which are among the artificial intelligence-based models, are preferred in many studies to predict different properties of concretes produced with different design parameters. Sah and Hong (2024) used ANN, support vector machine, multiple linear regression, and regression tree models to predict of concrete compressive strength using age, cement, water, superplasticizer, fly ash, blast furnace slag, coarse aggregate and fine aggregate. Yasin (2024) predicted of the dynamic shear modulus, dynamic modulus of elasticity, and dynamic poisson's ratio of concrete using ANN. A study was performed by Kumar and Kumar (2024) to predict Marshall stability of waste plastic reinforced concrete using ANN, support vector machine (SVM), random forest (RF), random tree (RT), and bagging RT. In their recently study, Salihi and Hamad (2024) explored the capabilities of ANN and gradient boosting-based predictive techniques in predicting the punching shear capacity of concrete slabs reinforced with FRP bars. In all of these studies and many other studies (Mosquera et al., 2024; Jaf et al., 2024; Harith et al., 2024; Duan et al., 2024), it is stated that ANN can be used to predict different properties of concrete and accurate prediction results could be achieved. Furthermore, ANN can help optimize concrete mix designs by predicting the best design parameters (cement, water, aggregate, and chemical and mineral additives) to meet many more performance criteria of concrete.

In this study, an ANN model was created to predict the compressive strength and mixing ratios of concrete for three different concrete classes (C30/37, C35/45, C40/50) and two different hydration days (7 days, 28 days). In the training and testing of the model created to predict the compressive strength of the ANN, 7 different inputs (hydration day, cement, water, high-performance superplasticizer, fine aggregate in the range of 0-4 mm, coarse aggregate in the range of 4-11.2 mm, coarse aggregate in the range of 11.2-22.4 mm) were used. In the estimation of the design parameters, the compressive strengths obtained from the experiments were used as input variables. Then, the experimentally determined results with ANN estimations were compared with R^2, MAPE and RMSE statistical methods and the obtained estimation results were discussed in the relevant sections.

MATERIAL AND METHODS

Material

CEM II/A-M (P-L) 42.5 R type cement (PC) manufactured by Ferpa Cement Plant (Kayseri) based on TS EN 197-1 (2012) standard was used as binder material. The chemical, physical and mechanical properties of PC determined according to the TS EN 196-2 (2013), TS EN 196-6 (2020), TS EN 196-3 (2017) and TS EN 196-1 (2016) standards are given in Table 1. The water used in the mixtures of the concretes is the municipal water in Kayseri province and conforms to TS EN 1008 (2003). Fine aggregate in the range of 0-4 mm, coarse aggregate in the range of 4-11.2 mm and 11.2-22.4 mm were used in the study, and tests for determining the physical properties of aggregates were carried out in accordance with the requirements of TS EN 1097-6 (2013), and given in Table 2.

As chemical additive, Conslumper 5170 S type high-performance superplasticizer additive was used. High-performance superplasticiser exhibited conventional dry material content of 16.20, relative density of 1.050, alkali content of 0.6%, pH value of 4.2.

Table 1. Properties of portland cement

Materials, PC	Analysis result	TSEN 197-1, requirements	Analysis method
Chemical properties, %			
SO_3	3.48	Max. 4.0	TS EN 196-2
Na_2O	0.23	-	TS EN 196-2
K_2O	0.32	-	TS EN 196-2
Total Alkali (Na_2O Equivalent)	0.44	-	TS EN 196-2
Cl^-	0.0110	Max. 0.10	TS EN 196-2
Physical and mechanical properties			
Specific gravity	3.10	-	TS EN 196-6
Specific surface (Blaine), cm^2/g	3471	-	TS EN 196-6
Volume expansion, mm	1.3	Max. 10	TS EN 196-3
Initial setting time, min.	146	Min. 60	TS EN 196-3
Compressive strength (2-day), MPa	28.2	Min. 20	TS EN 196-1
Compressive strength (28-day), MPa	51.9	Min. 42.5, Max. 62.5	TS EN 196-1

Table 2. Physical properties of aggregate

Physical properties	Aggregate, mm		
	0-4	4-11.2	11.2-22.4
Apparent particle density-q_a (Mg/m^3)	2.67	2.77	2.73
Particle density on an oven-dried basis-q_{rd} (Mg/m^3)	2.62	2.75	2.70
Particle density on a saturated and surface-dried basis- q_{ssd} (Mg/m^3)	2.64	2.76	2.71
Loose bulk density, (Mg/m^3)	1.70	1.375	1.349
Water absorption ratio, (%)	0.70	0.38	0.32

Methods

In this study, concrete samples of C30/37, C35/45 and C40/50 classes were produced at a concrete plant operating in Kayseri province between 2022 and 2024. For each concrete class, the compressive strength result of the concretes prepared for 20 different structural elements was obtained. The concrete samples were placed in 15 cm cube moulds during the casting of the ready-mixed concrete. These samples were kept in the moulds for 24 hours and then kept in a Jeotest brand curing pool in 23±2 °C water. On the 7th and 28th days, the compressive strengths of the samples taken from the curing pool were determined according to TS EN 12390-3 (2010). Mix designs for each concrete class are given in Table 3.

Table 3. Mixture designs of concrete classes

Concrete class	PC, kg/m^3	Water, kg/m^3	High-performance superplasticizer, kg/m^3	Aggregate (0-4 mm), kg/m^3	Aggregate (4-11.2 mm), kg/m^3	Aggregate (11.2-22.4 mm), kg/m^3
C30/37	310	140	4.03	950	255	700
C35/45	340	140	4.42	900	265	720
C40/50	380	140	4.94	900	270	720

Artificial neural networks

Artificial neural networks (ANN) are one of the widely used statistical methods that simulate the human brain and process data accordingly. The ANN model is based on layers called input layer, hidden layer and output layer. These layers are connected to each other through weights and biases (Jaf et al., 2024). The input layer contains a set of input nodes representing the input variables. The hidden and output layers contain the computational nodes and the output variable node, respectively (Beynood et al., 2015). As shown in Figure 1, the hidden layer can be more than one and each of them consists of neurons that are not directly connected to the input or output of the network (Kumar and Kumar, 2024). In very complex problems, it may be useful to use more than one hidden layer (Sevim et al., 2021). ANN learns from past or previously measured data, captures unknown data better than traditional statistical methods, and solves new problems without any prior knowledge of the nature of these interactions (Sakthivel et al., 2016). For this reason, ANN is used extensively in many fields of science to find solutions to different problems. For detailed information about ANN, different sources can be examined (Buscema, 2002; Grossi and Buscema, 2007; Kocak et al., 2023).

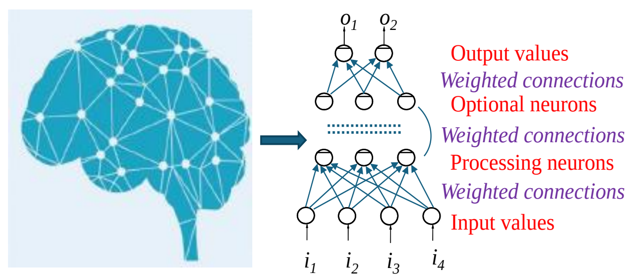

Figure 1. ANN's schematic diagram

Ann design and model parameters

The concrete classes used in the training and testing of these models consist of three classes: C30/37, C35/45, C40/50. The prepared concretes were used as columns, beams, decks and stairs. An Elman backpropagation neural network model was developed after different modelling to predict the compressive strengths and design parameters of the samples of concrete classes. In order to predict the compressive strength of the concretes in this model, seven parameters including hydration age (days), cement, water, hyperplasticising admixture, fine aggregate in the range of 0-4 mm, coarse aggregate in the range of 4-11.2 mm and coarse aggregate in the range of 11.2-22.4 mm constituted the input variables of the ANN model (Figure 2a). The compressive strength results obtained from the tests at 7 and 28-days were used as input to predict the design parameters (Figure 2b). The training parameter values of ANN models are given in Table 4.

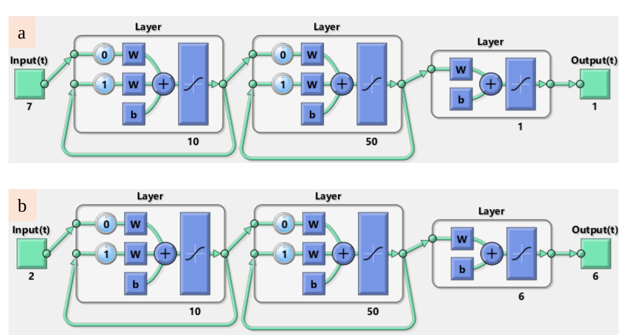

Figure 2. ANN's architectural network structure

Table 4. Training parameter values of the ANN model

Parameters	ANN-a	ANN-b
Input layer neuron numbers	7	2
Layer numbers	3	3
Hidden layer numbers	2	2
First hidden layer neuron numbers	10	10
Second hidden layer neuron numbers	50	50
Output layer neuron number	1	6

The minimum and maximum values of the input and output variables used in the ANN model for 1 m^3 concrete are given in Table 5.

A total of 240 compressive strength results obtained from 20 concrete pours of each concrete class and two sample results for each hydration day were used for training the ANN model. Of these results, 70% (168 data) were used for training and 30% (72 data) were used for testing. An equal number of samples were taken from each concrete class and hydration day data. The Randomisation function was used to objectively split test and training data and the initial seed value was set to 43.

Table 5. Input and output values used in ANN models (for 1 m^3 concrete)

Variable properties	Variables	Min.	Max.
Input or output	Ages, day	7	28
	Cement, kg/m^3	310	380
	Water, kg/m^3	140	140
	High-performance superplasticizer, kg/m^3	4.03	4.94
	Fine aggregate (0-4 mm), kg/m^3	900	950
	Coarse aggregate (4-11.2 mm), kg/m^3	255	270
	Coarse aggregate (11.2-22.4 mm), kg/m^3	700	720
Input or output	Compressive Strength, MPa	31.0	56.7

RESULTS AND DISCUSSION

The experimental results in the training and testing phases for each concrete class and the prediction performances of the ANN model are given in Figure 3.

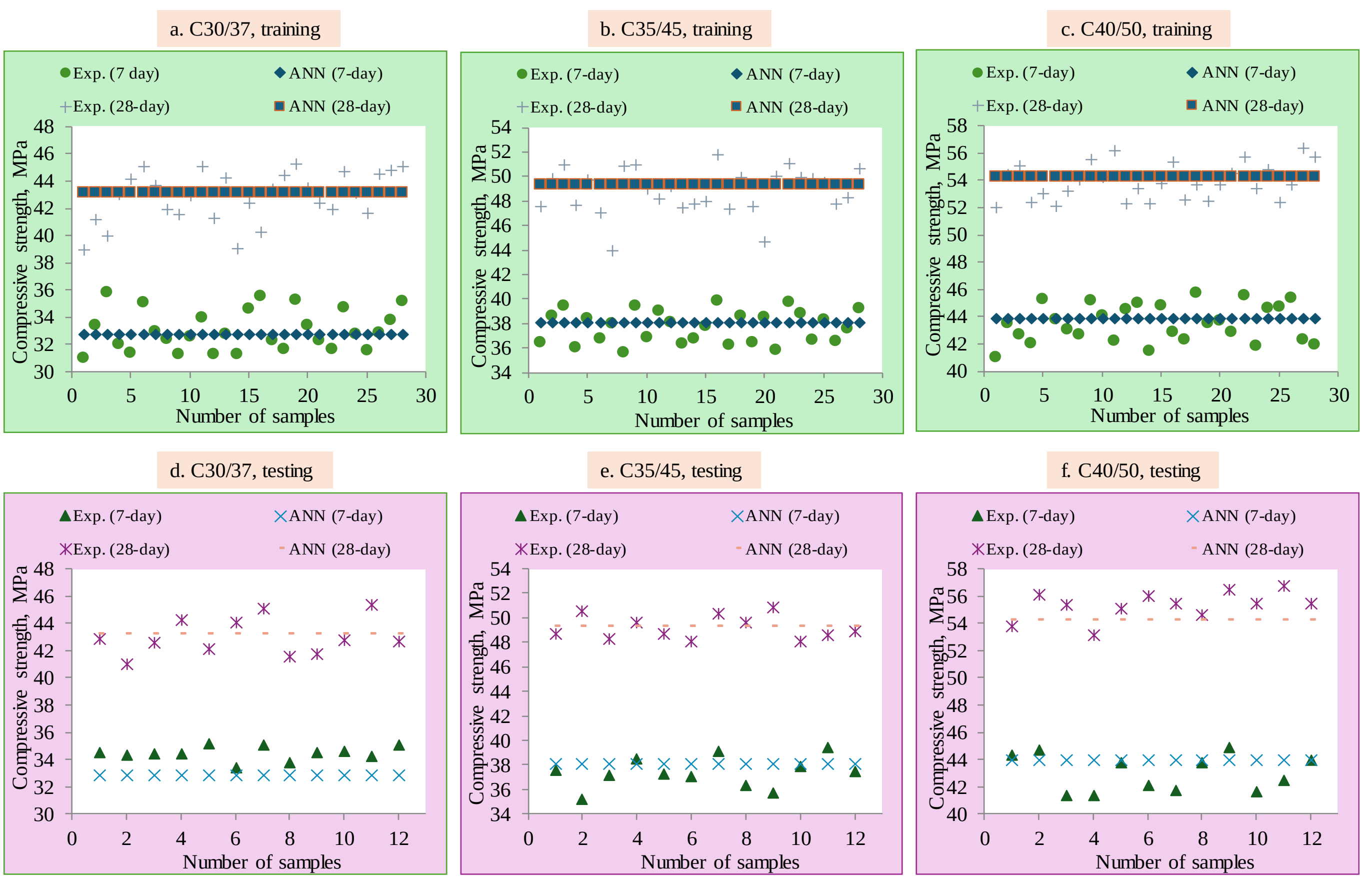

Figure 3. Experimental results in training and test phases and compressive strength prediction values obtained from ANN model

According to the experimental results, 7-day compressive strength results of C30/37, C35/45 and C40/50 concrete classes were in the range of 31.0, 35.2 and 41.0 MPa for the smallest values and 35.8, 39.8 and 45.7 MPa for the largest values, respectively (Figure 3). The 28-day compressive strength results, which determine the concrete classes, were in the range of 39.0, 44.0 and 52.0 MPa for the smallest values and 45.3, 51.8 and 56.7 MPa for the largest values, respectively (Figure 3). Therefore, since the samples were cube samples, it is seen that the smallest concrete strength values at 28th hydration day are above 37 MPa, which is the smallest value in C30/37 concrete class, 45 MPa, which is the smallest value in C35/45 concrete class, and 50 MPa, which is the smallest value in C40/50 concrete class. Therefore, it can be said that all concrete samples were produced in accordance with the standards according to the compressive strength results.

The prediction values obtained from the ANN model in the training and testing phase were 32.8, 38.0 and 43.9 MPa for 7-day compressive strength and 43.2, 49.3 and 54.2 MPa for 28-day compressive strength of C30/37, C35/45 and C40/50 concrete classes, respectively (Figure 3).

Coefficient of determination (R^2), mean absolute percentage error (MAPE) and root-mean squared error (RMSE) statistical methods were used to determine the reliability of the prediction values obtained from the experiments and models. These are shown in Equations (1), (2) and (3), respectively (Sakthivel et al., 2016; Aali et al., 2009).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - r_i)^2}{\sum_{i=1}^{N}(r_i - y_m)^2} \quad (1)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{N}\left|\frac{r_i - y_i}{r_i}\right| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - r_i)^2} \quad (3)$$

The R^2 results between the prediction values obtained from the ANN model in the training and testing phase and the actual results are given in Figure 4. Furthermore, the statistical results between the prediction values obtained from the ANN model used in the prediction of compressive strengths in the training and testing phase and the actual results are given in Table 6.

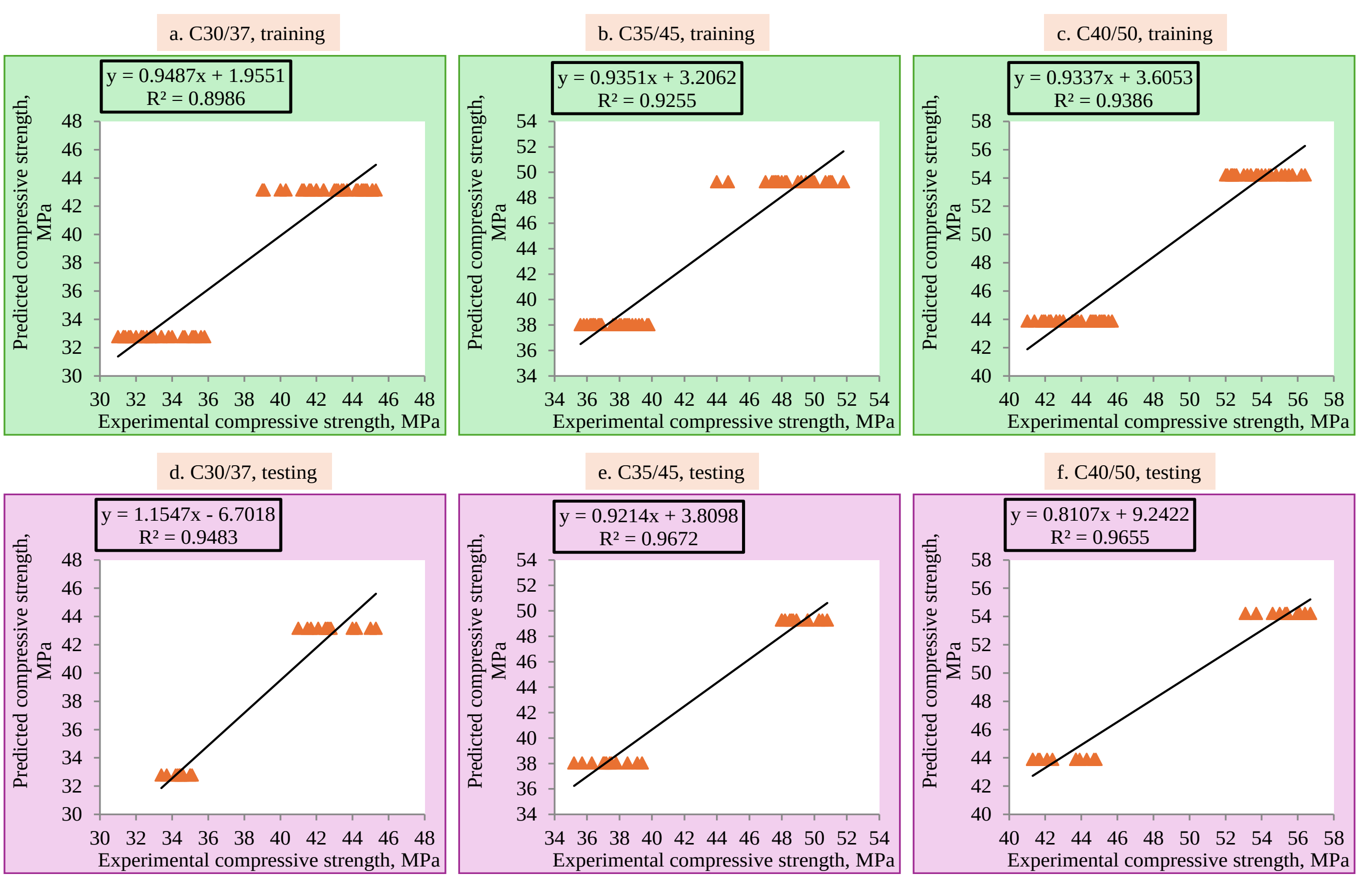

Figure 4. Coefficient of determination of compressive strength data during training and testing in ANN model

Table 6. Statistical results obtained from ANN model for compressive strengths

Concrete class	R^2	MAPE	RMSE
		Training	
C30/37	0.8986	$2.1x10^{-4}$	1.6743
C35/45	0.9255	$6.1x10^{-4}$	1.6403
C40/50	0.9386	$4.0x10^{-5}$	1.3412
		Testing	
C30/37	0.9483	$1.1x10^{-3}$	1.5378
C35/45	0.9672	$2.7x10^{-3}$	1.1938
C40/50	0.9655	$2.3x10^{-3}$	1.5259

It is seen that the R^2 values of ANN prediction results are (0.8986-0.9255-0.9386) in the training phase and (0.9483-0.9672-0.9655) in the test phase for C30/37, C35/45 and C40/50 concrete classes, respectively (Table 6). The MAPE values of these concrete classes were calculated as (0.00021-0.00061-0.00004) in the training phase and (0.00113-0.00273-0.00229) in the test phase, respectively (Table 6). RMSE values were calculated as (1.6743-1.6403-1.3412) in the training phase and (1.5378-1.1938-1.5259) in the test phase, respectively (Table 6). RMSE values were calculated as (1.6743-1.6403-1.3412) in the training phase and (1.5378-1.1938-1.5259) in the test phase, respectively (Table 6). It is seen that the R^2 value is very close to one in all models, but even the worst prediction value has an error of about 10%. When the MAPE results are considered, it is seen that the error rate is below 10% in all models of training and testing phases training, and even the worst prediction value can be predicted with an error rate of 0.27%, i.e. 99% accuracy. According to RMSE evaluations, it is seen that all models are close to 0. When the data obtained from the ANN model are evaluated as a whole, it can be said that compressive strength values can be determined with acceptable error rates.

In addition, the average of all samples taken during casting and used in training and testing were taken separately for each concrete class and hydration day in order to better see the agreement between the actual results and the prediction results. These values and the values predicted from the models are given in Figure 5.

According to these results, the compressive strengths of C30/37, C35/45 and C40/50 concrete classes for 7-day were predicted with an error of 2.13%, -1.05% and -1.36%, respectively. These values were predicted with errors of -0.69%, -0.81% and 0.18% for C30/37, C35/45 and C40/50 concrete classes for 28-day, respectively (Figure 5). Therefore, it can be stated that the compressive strengths predictions according to statistical indices and actual values are almost identical and both models can be used for such studies. In addition, the values of cement, water, high-performance superplasticizer, fine aggregate in the range of 0-4 mm, coarse aggregate in the range of 4-11.2 mm, coarse aggregate in the range of 11.2-22.4 mm, which are the output variables according to the compressive strengths desired to be obtained on the 7th and 28th day with the ANN model created, are given in Figure 6 for training and testing. In addition, the coefficient of determination values between the predicted results and the actual results in the training and testing phase are given in Figure 7. Furthermore, the statistical results determined between the prediction values obtained from the ANN model used in the prediction of the design parameters in the training and testing phase and the actual results are given in Table 7.

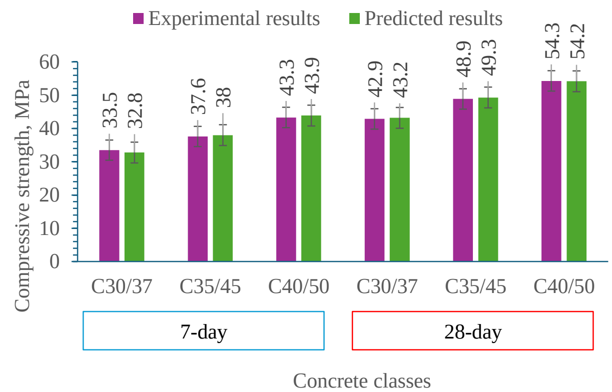

Figure 5. Comparison of average test results and predicted results for concrete classes

According to the modeling made during the training phase with ANN, it can be said that the R^2 value for any desired compressive strength can be predicted with 76% accuracy even in the determination of high-performance superplasticizer, which can be characterized as the most negative. According to MAPE values, it can be said that all values can be predicted with almost 100% accuracy and RMSE values are also very good. At the same time, it is seen that the mix quantities predicted during the test phase are very close to the actual values used in concrete designs (Table 7).

The design parameters obtained from training and testing were averaged in order to see more clearly the agreement between the real data and the prediction results. The actual values used in the design, the predicted values and the error rates in the predictions determined during the training phase are given in Table 8. According to Table 8, it is seen that the highest failure rate was 5.59% on day 7 in the high-performance superplasticizer of C35/45 concrete class. This result shows that even the amount of high-performance superplasticizer, which is one of the design parameters, can be predicted with 94% success (Table 8). Moreover, the error rates for the other hydration days and concrete classes are very close to 0. Therefore, it can be stated that both the compressive strengths and design parameters predicted according to statistical indices and actual values are very close to the actual values and the Elman backpropagation neural network model is very reliable and can be used successfully.

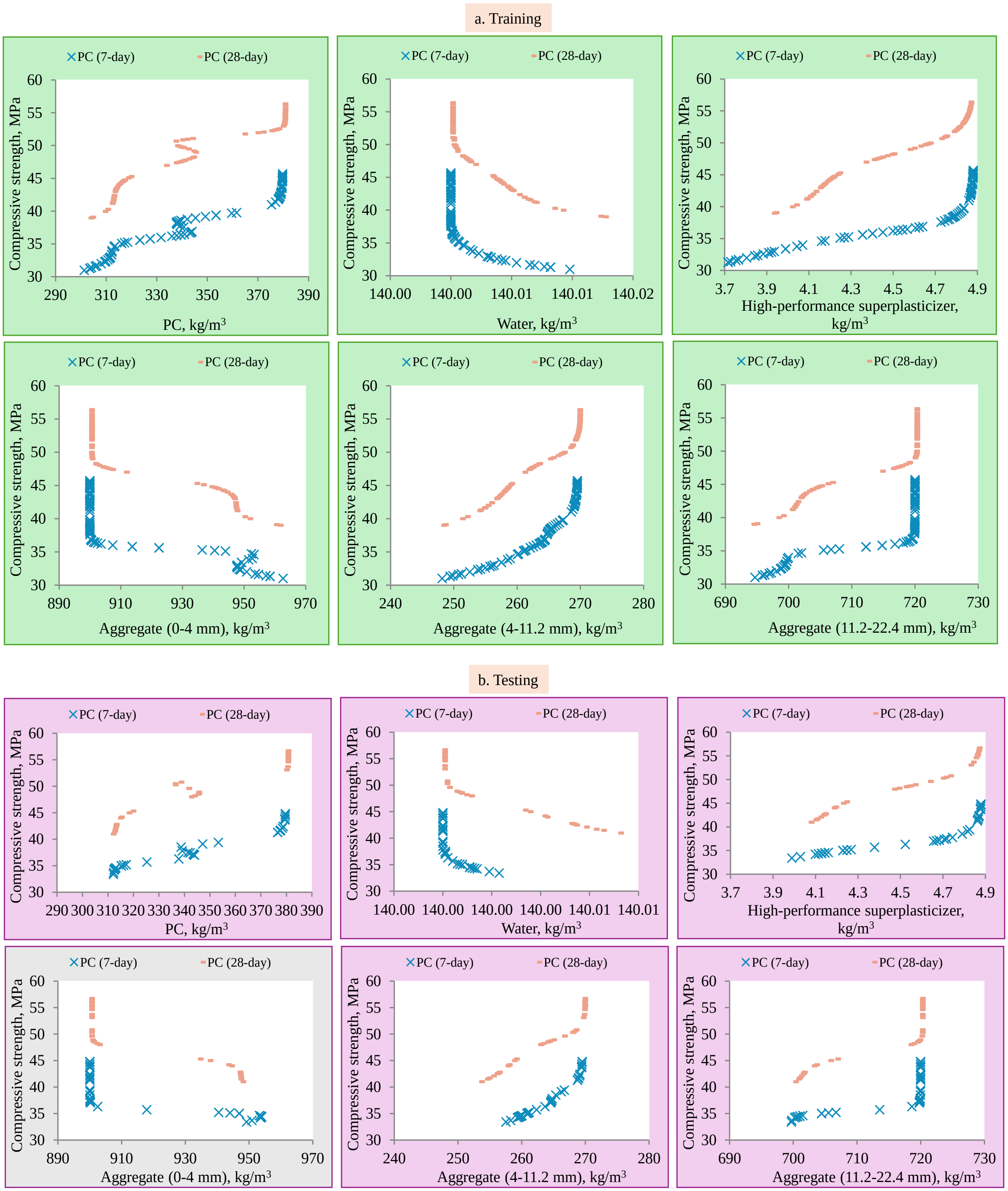

Figure 6. Predicted material mix quantities according to the desired compressive strength results

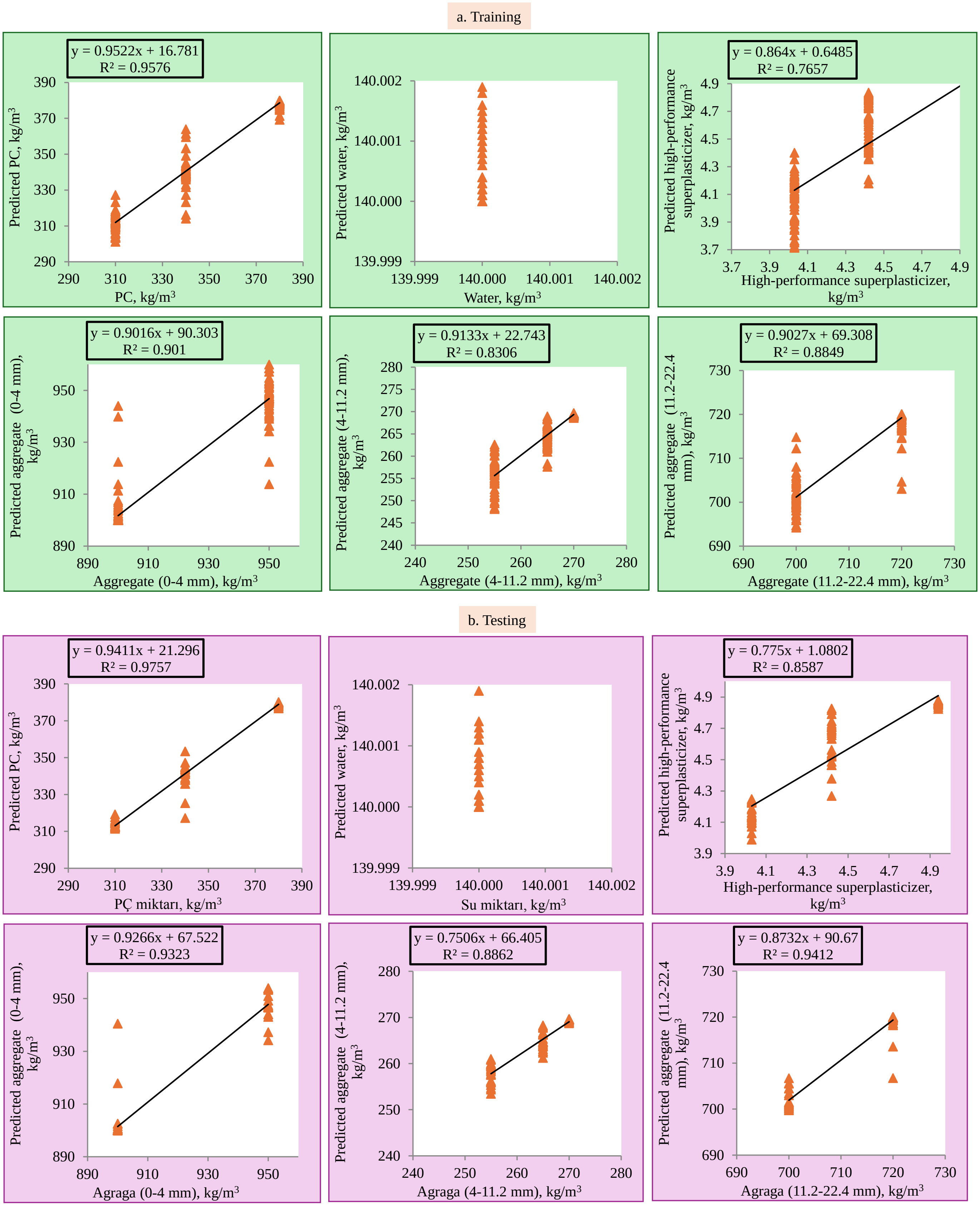

Figure 7. Coefficient of determination of the predicted material mix quantities according to the compressive strength results.

Table 7. Statistical results for design parameters

Design parameters, kg/m^3	PC	Water	High-performance superplasticizer	Aggregate (0-4 mm)	Aggregate (4-11.2 mm)	Aggregate (11.2-22.4 mm)
Training						
R^2	0.9576	1	0.7657	0.9010	0.8306	0.8849
MAPE	$1.7x10^{-6}$	$3.4x10^{-7}$	$2.1x10^{-4}$	$1.6x10^{-5}$	$1.3x10^{-4}$	$5.0x10^{-6}$
RMSE	5.9174	0.0032	0.1898	7.4184	2.6300	3.2065
Testing						
R^2	0.9757	1	0.8587	0.9323	0.8862	0.9412
MAPE	$1.0x10^{-4}$	$1.0x10^{-7}$	$4.4x10^{-4}$	$5.2x10^{-5}$	$3.1x10^{-4}$	$2.9x10^{-5}$
RMSE	4.7113	0.0022	0.1629	6.1405	2.3976	2.3905

Table 8. Comparison of predicted average results with actual design parameter results

Concrete class	Results	Design parameters						
		Day	PC, kg/m^3	Water, kg/m^3	High-performance superplasticizer, kg/m^3	Aggregate (0-4 mm), kg/m^3	Aggregate (4-11.2 mm), kg/m^3	Aggregate (11.2-22.4 mm), kg/m^3
C30/37	Predicted results	7	310.9	140	3.96	948.52	255.48	700.4
		28	313.18	140.01	4.14	945.07	255.81	701.93
	Exp. results	7 and 28	310	140	4.03	950	255	700
C35/45	Predicted results	7	341.58	140	4.68	902.01	264.86	719.14
		28	339.14	140	4.55	904.84	264.61	717.74
	Exp. results	7 and 28	340	140	4.42	900	265	720
C40/50	Predicted results	7	378.99	140	4.87	900	269.29	720
		28	378.35	140	4.83	900	269.43	720
	Exp. results	7 and 28	380	140	4.94	900	270	720
		Error, %						
C30/37	Predicted results	7	-0.29	0	1.9	0.16	-0.19	-0.06
		28	-1.01	0	-2.57	0.52	-0.32	-0.27
	Exp. results	7 and 28	-	-	-	-	-	-
C35/45	Predicted results	7	-0.46	0	**-5.59**	-0.22	0.05	0.12
		28	0.25	0	-2.83	-0.53	0.15	0.31
	Exp. results	7 and 28	-	-	-	-	-	-
C40/50	Predicted results	7	0.27	0	1.35	0	0.26	0
		28	0.44	0	2.24	0	0.21	0
	Exp. results	7 and 28	-	-	-	-	-	-

CONCLUSIONS

In this study, both compressive and design parameters of concrete classes C30/37, C35/45 and C40/50 were predicted by Elman backpropagation ANN model. A total of 240 experimental results were used for training and testing phases of the study.

According to the data obtained from the model to predict the compressive strength;

- According to the experimental results, the smallest compressive strength results of C30/37, C35/45 and C40/50 concrete classes at 28 days were obtained as 39.0, 44.0 and 52.0 MPa, respectively, and the smallest values of these concrete classes, 37 MPa, 45 MPa and 50 MPa, were achieved above the relevant standard requirements;
- The predicted values of C30/37, C35/45 and C40/50 concrete classes in the training and testing phase were 32.8, 38.0 and 43.9 MPa for 7-day compressive strength, 43.2, 49.3 and 54.2 MPa for 28-day compressive strength, respectively;
- The R^2 values of the ANN prediction results in the training and testing phase were calculated as (0.8986-0.9255-0.9386) and (0.9483-0.9672-0.9655) for the compressive strengths of C30/37, C35/45 and C40/50 concrete classes, respectively;
- Considering the MAPE results, the error rate is below 10% in all models in both the training and testing phase, and even the worst prediction value can be made with an error rate of 0.27% (99.73% accuracy);
- The RMSE values are calculated as (1.6743-1.6403-1.3412) and (1.5378-1.1938-1.5259) in the training and test phase, respectively, and are close to 0,
- It was determined that there was a significant consistency between the actual results obtained from the experiments and the prediction results. Moreover, the compressive strengths of concrete classes C30/37, C35/45 and C40/50 could be predicted with an error of 2.13%, -1.05% and -1.36% for 7 days and -0.69%, -0.81% and -0.18% for 28 days, respectively.

According to the data obtained from the model to predict the design parameters;

- For any desired compressive strength of C30/37, C35/45 and C40/50 concrete classes, the R^2 value can be predicted with 76% accuracy in the training phase and 85% accuracy in the test phase in determining the amount of high-performance superplasticizer that can be characterised as the most negative;
- The design parameters of these concrete classes can be predicted with 100% accuracy according to MAPE and RMSE values are also very good;
- When the actual results obtained from the experiments are compared with the average of the prediction results in the training phase, it is seen that the highest error is 5.59% on day 7 in the high-performance superplasticizer of C35/45 concrete class, while the other concretes can be predicted with almost 100% accuracy.

Therefore, when these results are evaluated as a whole, it can be stated that the Elman backpropagation neural network model is reliable and can be used successfully in the prediction of both compressive strengths and design parameters

DECLARATIONS

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Data availability

The data supporting the findings of this study are presented in the forms of Tables and Figures in the text.

Author’s contribution

Fatma KARS: Investigation, Methodology, Writing – original draft, Resources;

Giyasettin Ozcan: Investigation, Methodology, Writing – review & editing;

Eyyup GULBANDILAR: Methodology, review & editing, Supervision.

Yilmaz KOCAK: Investigation, Methodology, Visualization, Writing – review & editing.

Competing interests

The authors declare no competing interests in this research and publication.

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