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Prediction of concrete compressive strength due to long term sulfate attack using neural network

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KEYWORDS

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Abstract This work was divided into two phases. Phase one included the validation of neural network to predict mortar and concrete properties due to sulfate attack. These properties were expansion, weight loss, and compressive strength loss. Assessment of concrete compressive strength up to 200 years due to sulfate attack was considered in phase two. The neural network model showed high validity on predicting compressive strength, expansion and weight loss due to sulfate attack. Design charts were constructed to predict concrete compressive strength loss. The inputs of these charts were cement content, water cement ratio, C_3A content, and sulfate concentration. These charts can be used easily to predict the compressive strength loss after any certain age and sulfate concentration for different concrete compositions.

1. Introduction

The service life of concrete structures is affected by the exposure to severe environmental conditions. In fact, among the different types of attack of concrete structures, sulfates are the most widely exposing [1]. The reduction in compressive strength and expansion is a direct effect of sulfate exposure. The prediction of concrete structures service life needs an overview on the properties of concrete for a long time due to sulfate attack. The assessment of concrete properties due to sulfate attack using experimental methods is limited to short time nearly 700 days [2,3]. The long term concrete properties need a more appropriate method [4].

Numerical modeling methods such as neural networks are being increasingly used in civil engineering applications, especially for the purpose of interpolating concrete properties [5–7].

Polynomial interpolation is inappropriate and may yield unsatisfactory results when it is used to predict intermediate values. Linear regression can exclude illegitimate results. The numerical modeling regression methods are the best methods to predict concrete experimental results due to their multi-parameters [8,9].

More appropriate strategies for such cases are derived as an approximating function that fits the shape or general trend of

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Table 1 Ranges of used variables in database.

	Minimum	Maximum
Input variables		
Cement content, CC (kg/m^3)	207	532
Water cement ratio (w/c)	0.28	0.73
C_3A (%)	Zero	17
Sulfate concentration, SO_3 (%)	Zero	10
Initial compressive strength, $F_{c\ int}$ (MPa)	16.5	78.4
Period of immersion (days)	7	16,425
Output variables		
Compressive strength (MPa)	16.0	66.46
Expansion ($\times10^{-4}$)	0.08	110
Weight loss (%)	0.074	6.30

the data without necessarily matching the individual points. Artificial neural network is the development of multiple regression methods. Although such approaches have common sense appeal and are valid for very complex calculations, they are deficient because they are arbitrary. Therefore, expectation of long term concrete properties is very difficult with these approaches. To remove this subjectivity, some criterion must be advised to establish a basis for the predicting [8,9]. A technique for accomplishing this objective, called *interpolation regression*, is discussed in this paper.

2. Artificial Neural Networks (ANNs)

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. Neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output [10,11].

Neural network is adjusted, based on a comparison of the output and the target, when the network output matches the target. Typically, many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields that are difficult for conventional computers or human beings [12,13].

3. Structural applications of neural network

In recent years ANN could be trained to solve problems that are difficult for conventional computers or human brains. ANN has been applied to many other fields such as; aerospace, automotive, banking, credit card activity checking, defense, electronics, entertainment, financial, industrial, insurance, manufacturing, medical, oil and gas, robotics, speech, securities, telecommunications, transportation, and civil engineering [14,15].

Today, ANN has been applied to many civil engineering problems with some degree of success such as detection of structural damage, structural system identification, modeling of material behavior, structural optimization, structural control, ground water monitoring, prediction of settlement of shallow foundation, concrete mix proportions, and predicting properties of conventional concrete and high performance concretes [15,16]. Ozcan et al. [10] used neural networks to predict long-term compressive strength of silica fume concrete. Topcu and Sarıdemir [15] predicted properties of waste autoclaved aerated concrete aggregate using artificial neural network.

Saridemir [7] studied the use of neural network for developing a methodology for predicting compressive strength of concrete with different w/c ratios. They arranged the data used in the neural network model in a format of five input parameters that cover the water-to-binder ratio, binder sand ratio, metakaolin percentage, superplasticizer percentage, and age. The proposed neural network model predicts the compressive strength of mortars only.

The use of neural networks to predict the concrete durability is the logic development in structural damage detection. Concrete durability due to chloride or sulfate attack was modeled by neural networks. Topcu et al. [5] used back propagation neural networks to predict the corrosion current in reinforced concrete, in which fly ash was used. They concluded that, the neural network models performed better than the multiple regression ones, especially in reducing the scatter of predictions.

Yaprak et al. [11] used the neural network to predict compressive strength of concrete. Yaprak et al. arranged the data used in the neural network model in a format of four input parameters that cover the water-to-binder ratio, cement content, curing conditions, and age. Also, Pann et al. [16] used neural networks for predicting the 28 day compressive strength of Portland composite cement.

Table 2 References of mortar and concrete data set.

Model no.	Data set	Sulfate type	Output variable	Reference numbers
1-a	Concrete	Mg	Compressive strength	[19–21,29,31,35,53,54]
1-b	Mortar	Mg	Compressive strength	[19–21,26,30,43,44,55]
2-a	Concrete	Mg	Expansion	[19–21,37,53]
2-b	Mortar	Mg	Expansion	[19–22,41,43]
3-a	Concrete	Mg	Weight loss	[19–21,29]
3-b	Mortar	Mg	Weight loss	[19–21]
4-a	Concrete	Na	Compressive strength	[23,29,31,34–36,38,42,45,47,50,52,56]
4-b	Mortar	Na	Compressive strength	[26,30,36,44,46,55]
5-a	Concrete	Na	Expansion	[23–25,28,32–34,37–40,48,50,51]
5-b	Mortar	Na	Expansion	[22,24,27,33,41,49]
6-a	Concrete	Na	Weight loss	[24,29,16]
6-b	Mortar	Na	Weight loss	[32]

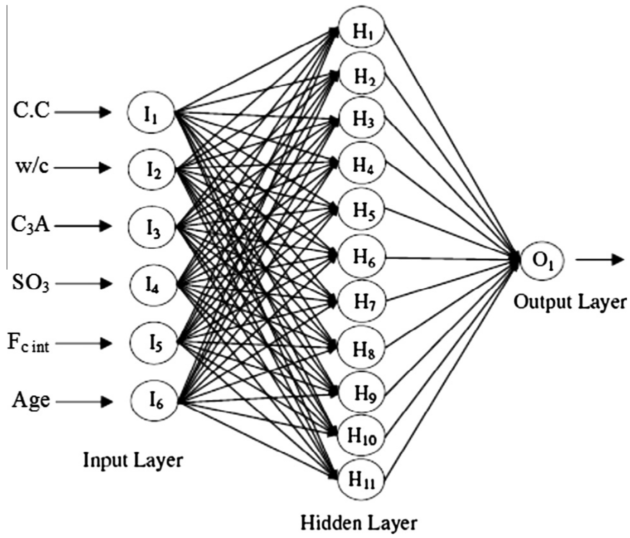

Figure 1 The chosen model architecture.

Goktepe et al. [13] studied the effect of sulfate attack on the expansion of mortar for a long term period of time using neural networks. Orejarena and Fall [6] focused on studying the use of artificial neural networks to predict the effect of sulfate attack on strength of cemented paste. The neural networks model was composed of five input parameters. These parameters were the cement content, slag content, binder ratio, water cement ratio, and sulfate content. The output parameter was compressive strength. The authors explained that NNs have strong potential as a feasible tool for evaluation of the effect of sulfate attack on the compressive strength of concrete.

4. Program and model developing

Concrete structures exposed to sulfates attack generally deteriorate due to formation of gypsum and ettringite. This deterioration leads to decrease in compressive strength, weight loss, and volume increase (expansion) [17,18].

In this section, a neural network model is developed to predict the concrete properties vs. time due to sulfate attack. Multilayer feedforward network models have been trained with Levenberg–Marquardt training algorithm [10,11]. The data used for calibrating and validating of the neural network were collected from the experimental studies of many published papers [19–56].

4.1. Data collecting and grouping

The used data were collected from 38 different documented published papers [19–56]. Among those, 2000 records were used for training, testing, and validating phases of neural

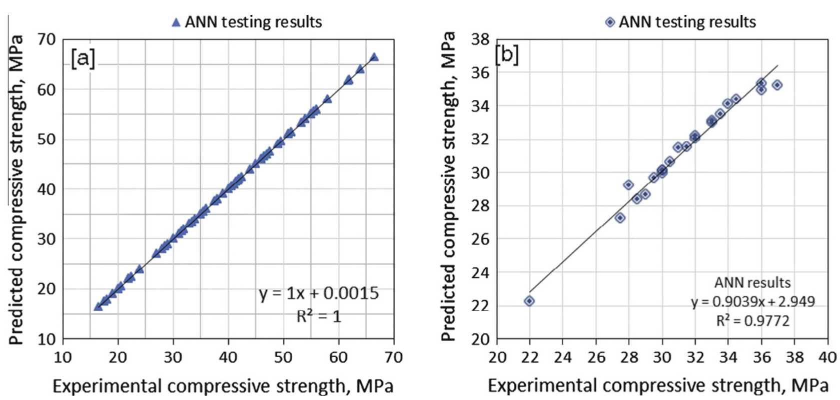

Figure 2 Model 1 predicted vs. experimental compressive strength for testing data (a – concrete, b – mortar) subjected to Mg^{2+} sulfate ions.

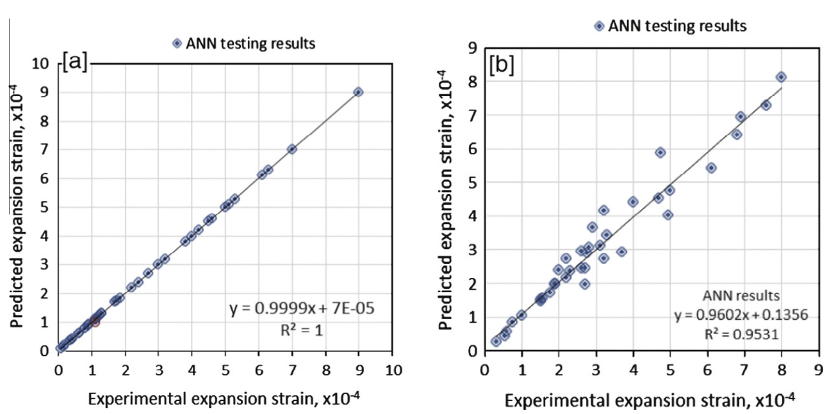

Figure 3 Model 2 predicted vs. experimental linear expansion for testing data (a – concrete, b – mortar) subjected to Mg^{2+} sulfate ions.

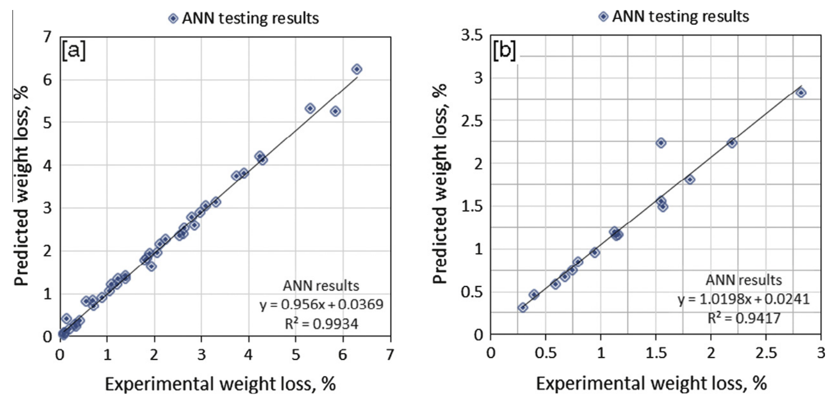

Figure 4 Model 3 predicted vs. experimental weight loss for testing data (a – concrete, b – mortar) subjected to Mg^{2+} sulfate ions.

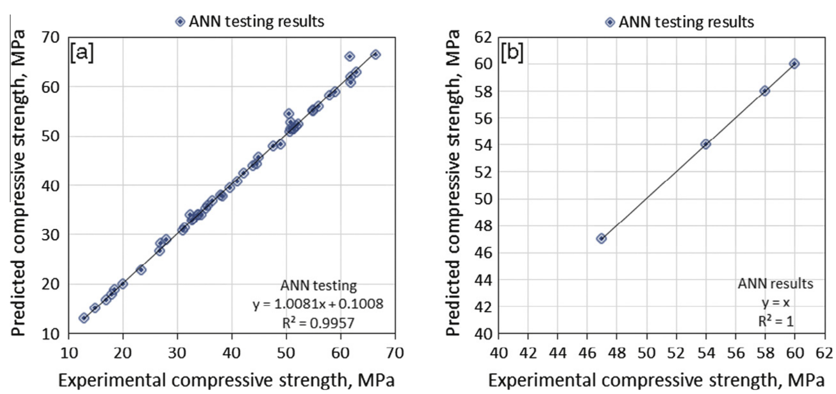

Figure 5 Model 4 predicted vs. experimental compressive strength for testing data (a – concrete, b – mortar) subjected to Na^{+} sulfate ions.

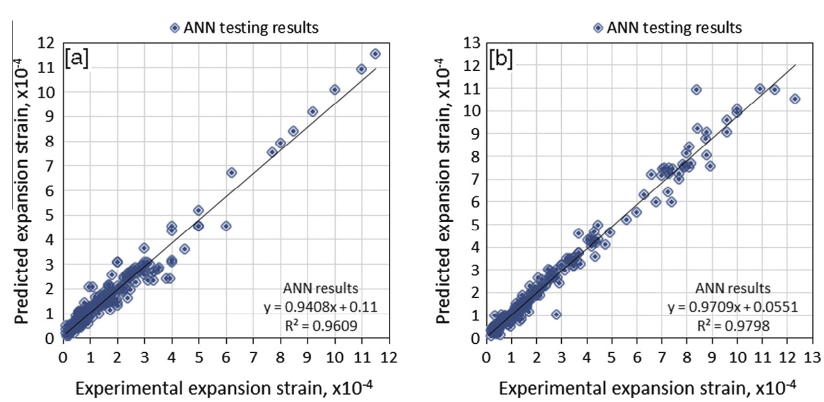

Figure 6 Model 5 predicted vs. experimental linear expansion for testing data (a – concrete, b – mortar) subjected to Na+ sulfate ions.

network models. In these models, six inputs and one output were estimated for each case study. The inputs include the amount of cement per unit concrete volume, water cement ratio, C_3A content, sulfate type and solution concentration, initial compressive strength, period of immersion in solution. The model output variables were compressive strength, expansion, and weight loss. The available data set was divided into two main groups (mortar and concrete). The ranges of the used variables in the database are presented in Table 1, while Table 2 presents the considered references for each model.

4.2. Artificial neural network architecture

Before proceeding with model development, some model parameters were selected based on similar studies and the literature available [10–12]. The total database size in the present

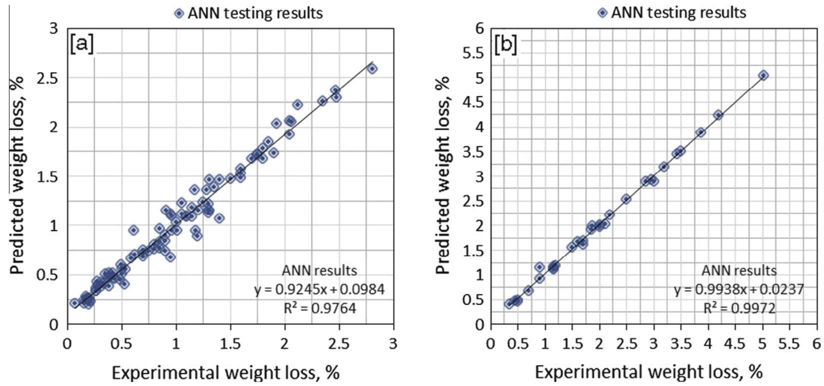

Figure 7 Model 6 predicted vs. experimental weight loss for testing data (a – concrete, b – mortar) subjected to Na+ sulfate ions.

Table 3 The statistical values of proposed models.

Model no.	ANN		
	RMS	R^2	MAPE
1-a	0.003	0.999	0.002
1-b	0.560	0.977	1.040
2-a	0.001	0.999	0.010
2-b	0.425	0.953	10.00
3-a	0.150	0.993	13.57
3-b	0.174	0.942	5.360
4-a	0.970	0.996	1.120
4-b	0.000	1.000	0.000
5-a	0.350	0.961	24.42
5-b	0.396	0.980	16.86
6-a	0.116	0.976	16.34
6-b	0.064	0.997	3.530

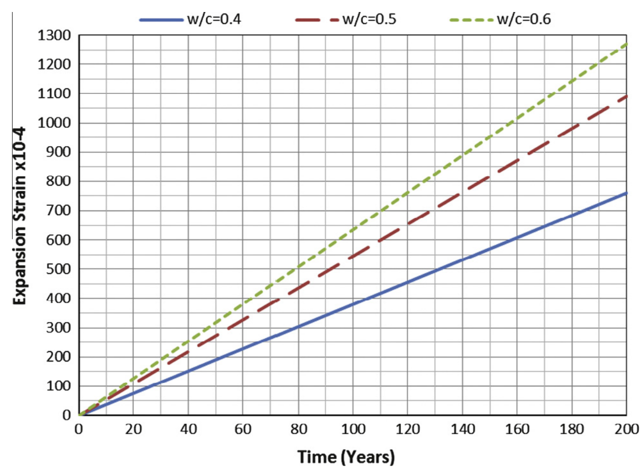

Figure 8 Prediction of expansion vs. time for 9.0% C_3A.

study was 2000 cases, considering 6 inputs and one output for each model. These data are divided into 80% for training, 10% for testing (also called verification) and 10% for validation [10]. The preliminary architecture of the neural network according to MATLAB manual, see Fig. 1 was conceived as follows:

(a) ***Type of neural network:*** Multilayer perceptron feed-forward was trained through the error back-propagation algorithm (this is the most commonly used type of ANN and its application to function approximation has already been proven in several studies) [10–12].
(b) ***Neurons in the first layer:*** Six neurons were specified using MATLAB manual according to model size.
(c) ***Hidden layers:*** It has been found that a single hidden layer presents satisfactory results for many problems [10].
(d) ***Neurons in hidden layer:*** Eleven neurons were specified from empirical criteria [10].
(e) ***Number of outputs:*** Single output in every model (compressive strength, expansion, weight loss).

The commercial software MATLAB® was used for the development of the model. A script was developed and adjusted several times until the error criteria were met. It was found that by increasing the number of hidden neurons

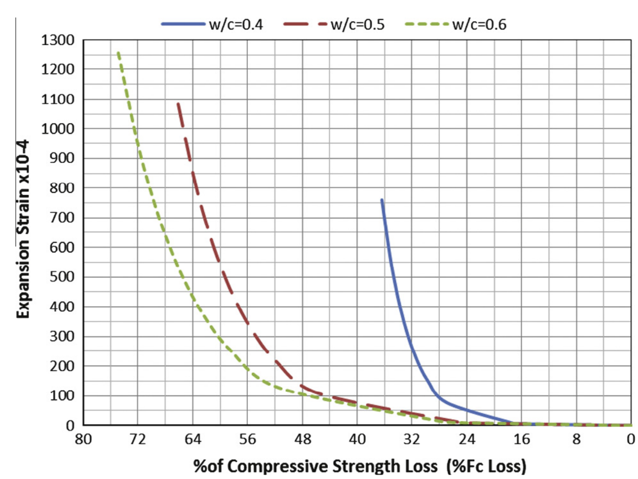

Figure 9 Prediction of compressive strength loss vs. expansion for 9.0% C_3A.

to 12 instead of 11, the convergence of the model improved drastically. In order to avoid overtraining of the network, the training was stopped when the testing error increased. This

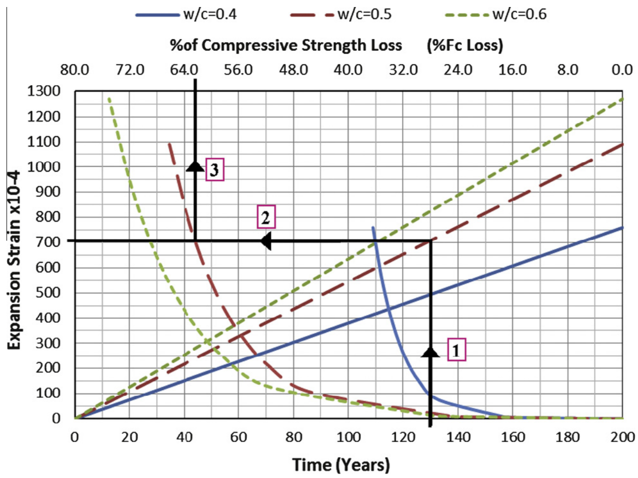

Figure 10 Expansion–time and expansion–compressive strength loss relation of concrete with 350 kg/m^3 cement content and 5.0% C_3A subjected to 5% Mg^{2+} sulfate ions.

feature is automatically set up in the software. The training of the network was stopped when the error factor in each vector (training, validation and testing) was equal/less 5% [10]. The training method used in the model development was the Levenberg–Marquardt algorithm which exhibits the fastest convergence in similar problems [10].

5. Results and discussion

In the present study, three forms were used to comparative evaluation of the performance of the multilayer feed-forward neural network model. These forms are root-mean-squared (RMS) error, absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) as given in Eqs. (1)–(3). These forms were calculated between model's results and experimental results [10]:

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

$$R^2 = \frac{\left(n\sum_i^t o_i - \sum_i^t \sum_i^o\right)^2}{\left(n\sum t_i^2 - (\sum t_i)^2\right)\left(n\sum o_i^2 - (\sum o_i)^2\right)} \tag{2}$$

$$\mathrm{MAPE} = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}|t_i - o_i|}{\sum_{i=1}^{n} t_i} \times 100\right] \tag{3}$$

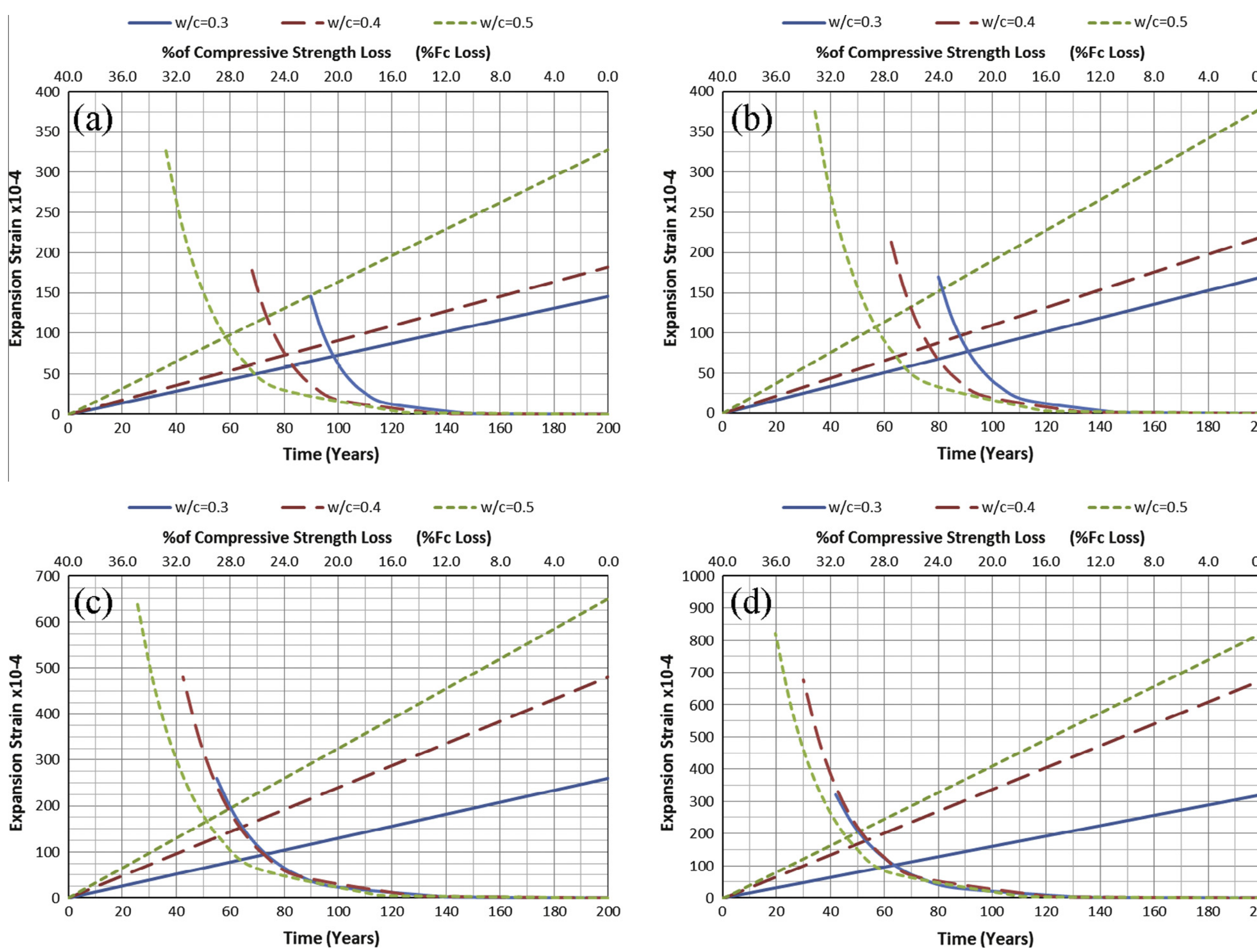

Figure 11 Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 5% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 2.0% C_3A. (c) 5.0% C_3A. (d) 9.0% C_3A.

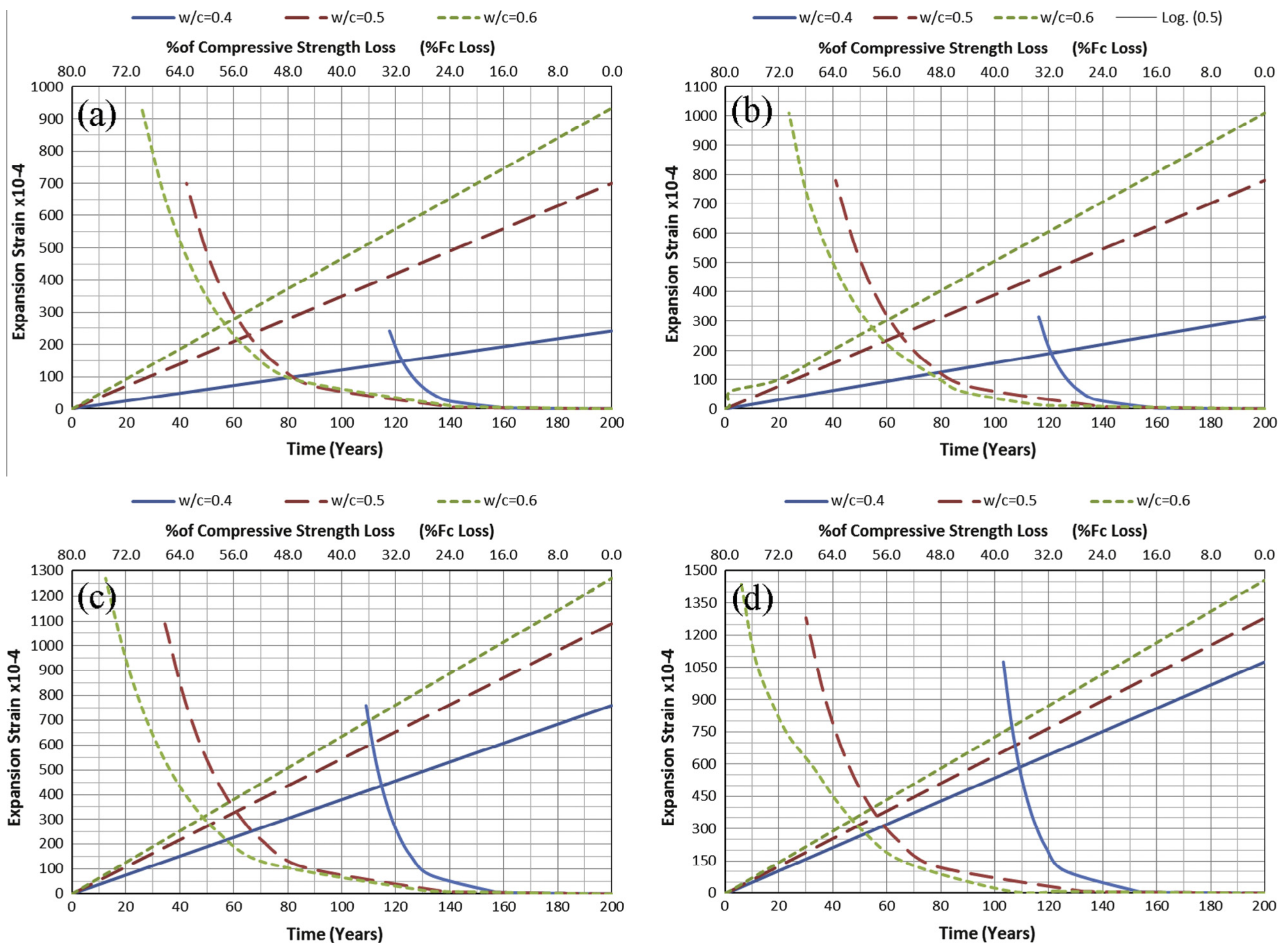

Figure 12 Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 5% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 2.0% C_3A. (c) 5.0% C_3A. (d) 9.0% C_3A.

where t is the target value, o is the output value, n is the pattern. In the present study, compressive strength, expansion, and weight loss vs. time due to sulfate attack were predicted using the multilayer feed-forward neural network model. In the training and testing processes experimental data from thirty-eight different sources were used [19–56]. All results, obtained from experimental studies and the predicted values for compressive strength, expansion, and weight loss vs. time are shown in Figs. 2–7.

From these figures, the values obtained from the training and testing using the ANN model were very close to the experimental results. The results of ANN model demonstrate that the ANN system can be successfully applied to establish accurate and reliable prediction models. The statistical parameter values of RMS, R^2 and MAPE showed obviously this behavior. The statistical values of RMS, R^2 and MAPE including all the ANN models, is given in Table 3. The best R^2 value obtained is 1.000 for training set ANN, while, the minimum value of R^2 is 0.942 for testing set ANN.

6. Interpolation regression of concrete compressive strength using ANN

In this section, an attempt to predict the concrete compressive strength for a long age due to sulfate attack is developed based on the experimental results that were extracted from many published papers [19–56]. Neural network is used herein to predict this relation up to 200 years.

The estimation of concrete compressive strength in one model gives scatter output results due to different types of sulfate attack using concrete water cement ratio, cement content, C_3A, degree of sulfate exposure, and time. So, in this approach, the estimation of concrete compressive strength due to sulfate attack is divided into two stages. Stage one includes estimation of relation between age, and expansion for different mentioned variables using neural network. Relation between expansion and concrete compressive strength loss is established using neural network in the second stage.

In this model, compressive strength loss is used instead of compressive strength values because expansion and compressive strength loss increase in one direction vs. time where compressive strength values decreases as time increases. So, the use of compressive strength loss seems to be reliable in the proposed model. Using neural network model, relation between expansion strain and time of exposure is estimated. Fig. 8 shows an example for concrete with 350 kg/m^3 cement and 5.0% C_3A subjected to 5.0% sulfate attack.

Fig. 9 shows the relation between expansion strain and concrete compressive strength loss. Figs. 8 and 9 are merged together in Fig. 10 which shows the relation between time

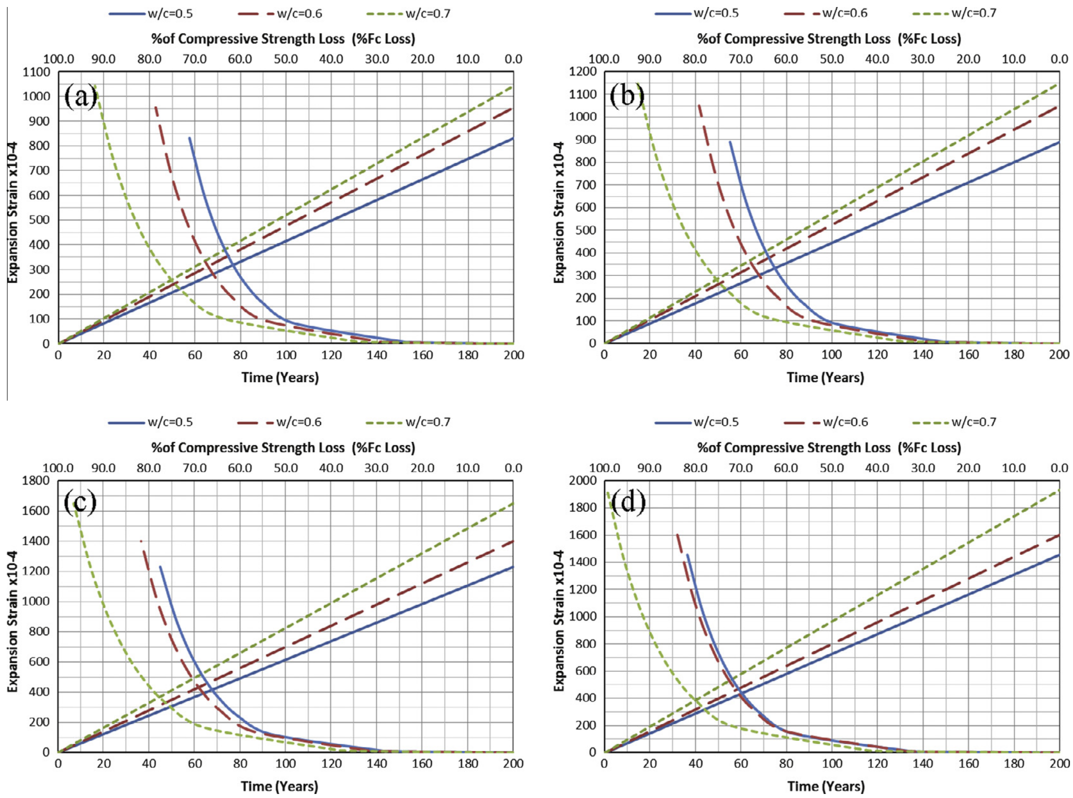

Figure 13 Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 5% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 2.0% C_3A. (c) 5.0% C_3A. (d) 9.0% C_3A.

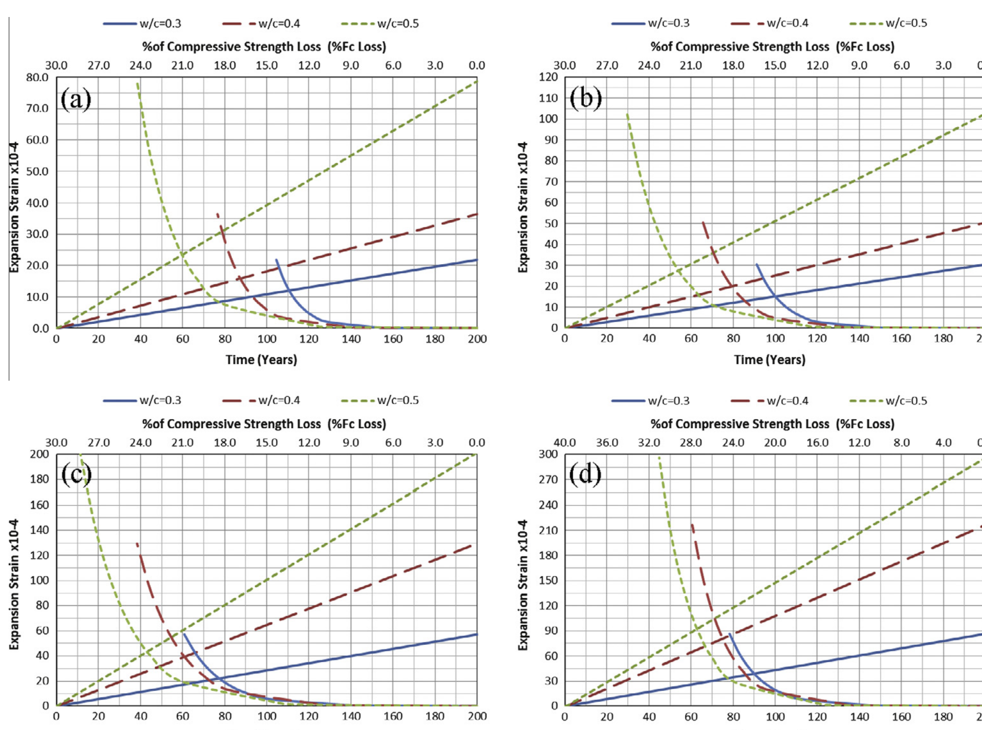

Figure 14 Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 5% Na^+ sulfate ions (a) 0.2% C_3A. (b) 2.0% C_3A. (c) 5.0% C_3A. (d) 9.0% C_3A.

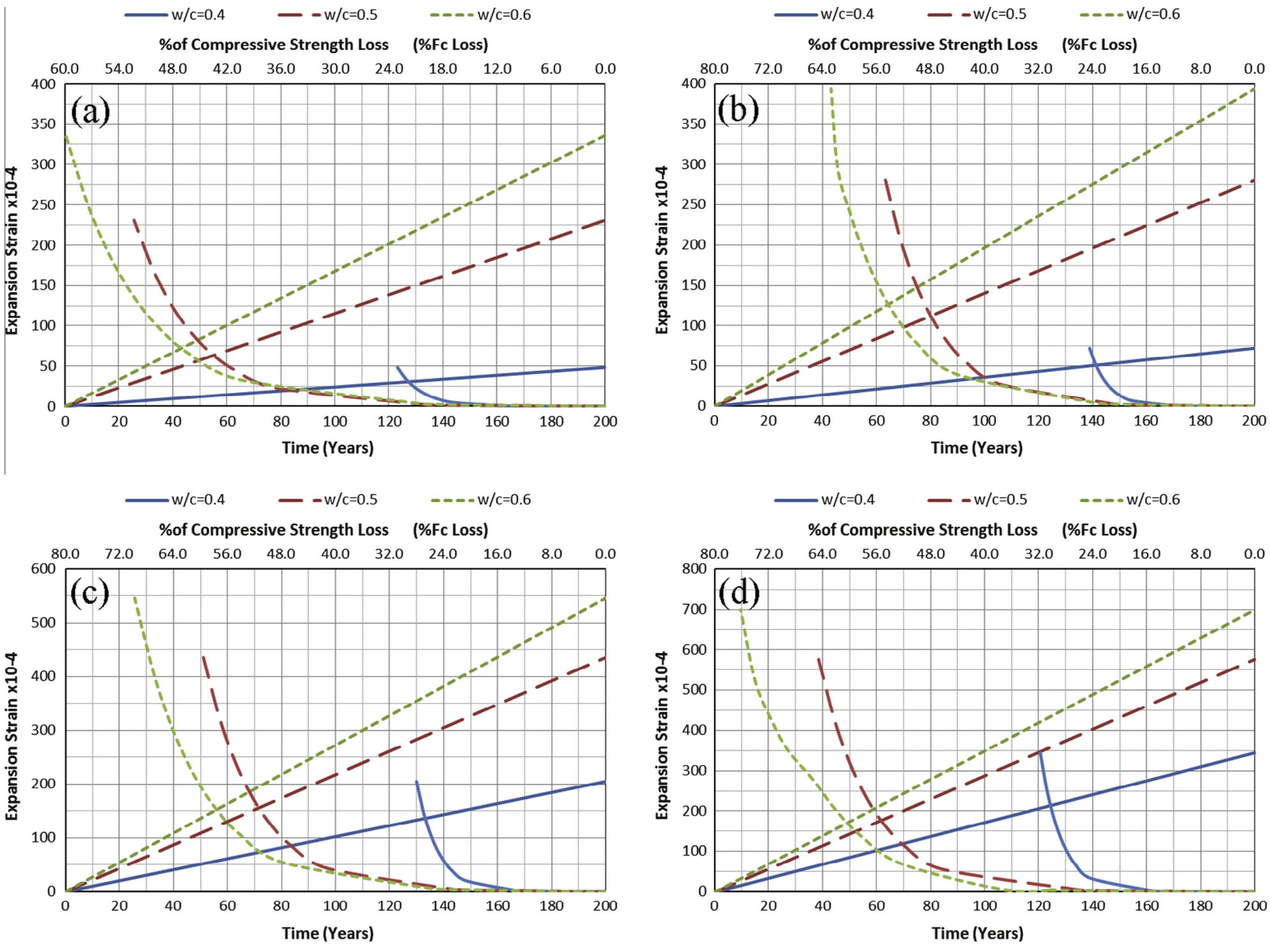

Figure 15 Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 5% Na$^+$ sulfate ions (a) 0.2% C_3A. (b) 2.0% C_3A. (c) 5.0% C_3A. (d) 9.0% C_3A.

and expansion for different w/c (straight lines) and relation between expansion and compressive strength loss (curves) for the same w/c. This figure is presented for concrete having cement content of 350 kg/m^3 9.0% C_3A and subjected to 5.0% Mg sulfate attack.

According to Fig. 10, the procedures for determining the concrete compressive strength loss% for concrete with 9.0% C_3A and 0.5w/c after 130 years are carried out according to the following steps:

1. Age 130 years.
2. Using the relation between expansion strain and age at 0.5 w/c ratio, expansion strain can be estimated as 700×10^{-4}.
3. Using an expansion of 700×10^{-4} and expansion–compressive strength loss relation. The expected compressive strength loss percentage can be estimated as 62%. These steps are summarized in Fig. 10.

6.1. Design charts for estimating concrete compressive strength loss using neural network

The aim of this proposed model is to present a new application approach for estimating concrete compressive strength loss due to sulfate attack. Design charts are established to estimate the compressive strength loss for different cases. The design charts are designed using zones limits of ACI 201 and ACI 318 [57,58].

ACI 318 divides sulfate attack to four zones according to the sulfate concentration and recommends specified mix properties for each zone [57,58]. The proposed durability design charts can be presented according to the following items:

1. ***Cement content and water cement ratio.*** Cement content of 300, 350, and 450 kg/m^3 are used. Three values of w/c are specified for each cement contents; (0.3, 0.4, and 0.5 for 450 kg/m^3, 0.4, 0.5, and 0.6 for 350 kg/m^3, and 0.5, 0.6, and 0.7 for 300 kg/m^3).
2. ***C_3A content.*** Four values are used as 0.2%, 2.0%, 5.0%, and 9.0%.
3. ***Sulfate concentration.*** SO_3 concentrations are specified as 0.2%, 1.0%, and 5.0%.
4. ***Type of ions.*** Sodium and magnesium sulfates are used.

Using the concept of neural network presented in Fig. 10, design charts for different parameters mentioned previously are constructed as shown in Figs. 11–28. These charts show the relation between percentage of concrete compressive strength loss and age related with expansion. The cement content in these charts varies from 300 to 450 kg/m^3 while

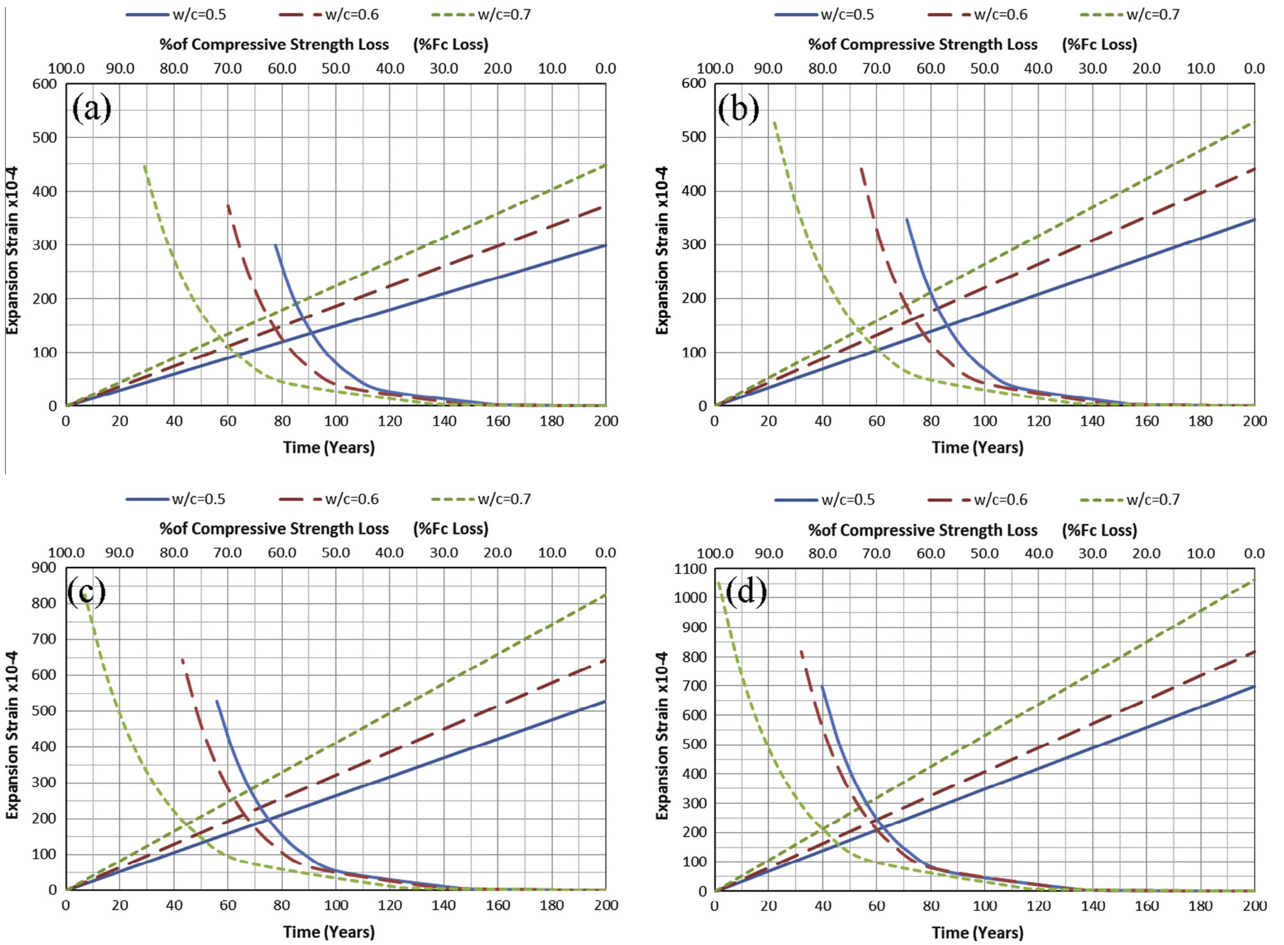

Figure 16 Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 5% Na^+ sulfate ions (a) 0.2% C_3A. (b) 0% C_3A. (c) 5.0% C_3A. (d) 9.0% C_3A.

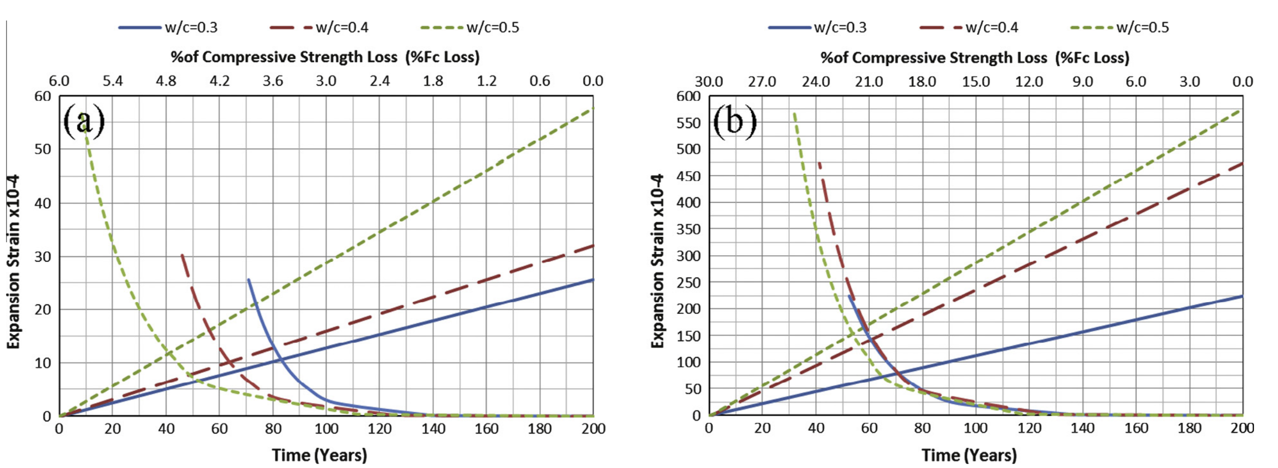

Figure 17 Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 1.0% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

C_3A content varies between 0.2% and 9.0%. The effect of sulfate ions type is considered in these charts.

The previous charts provide an easy method to estimate concrete compressive strength loss and linear expansion strain for any specified concrete proportions. As an example, estimation of the compressive strength loss for concrete with w/c = 0.5, and C_3A = 5.0% subjected to 5.0% Mg sulfate attack can be determined using Figs. 11–13. The compressive strength loss after 150 years is 16%, 31%, and 37% for cement content with 450, 350, and 300 kg/m^3, respectively.

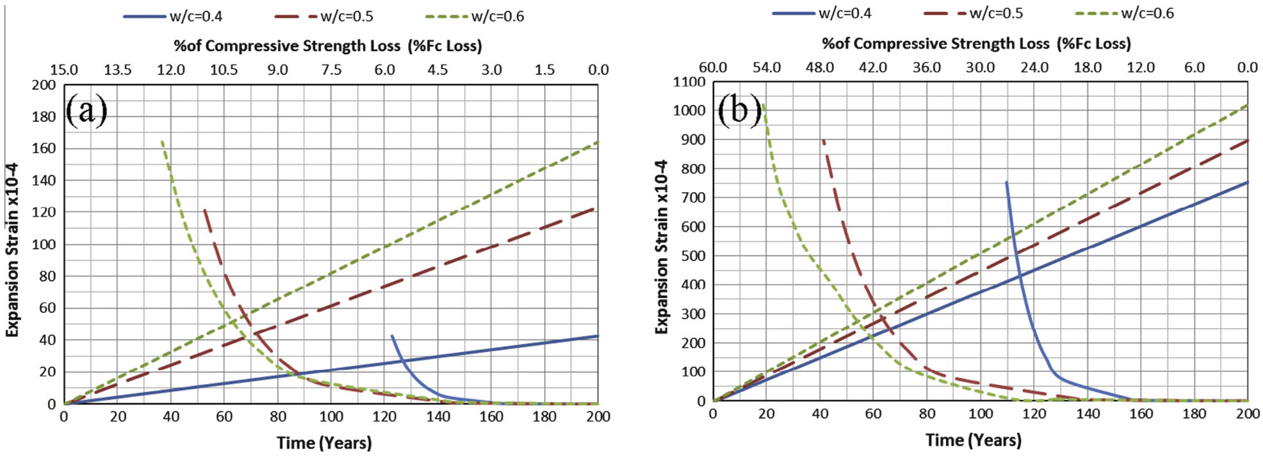

Figure 18 Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 1.0% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

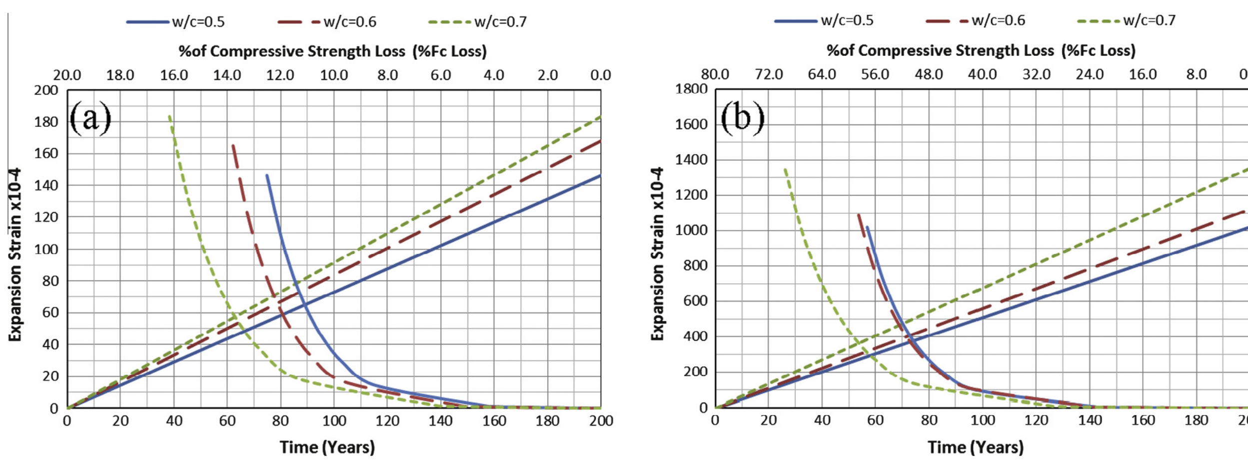

Figure 19 Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 1.0% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

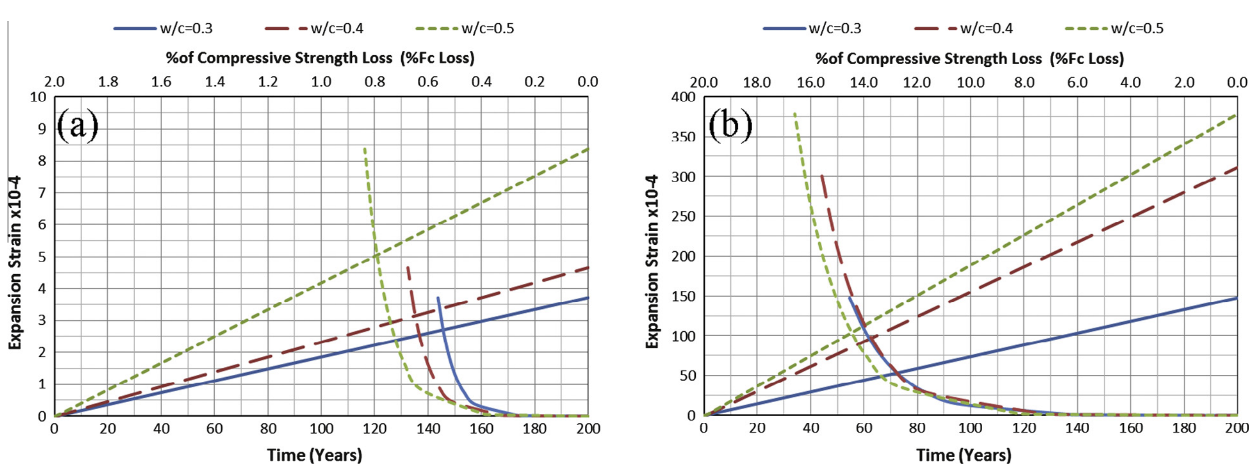

Figure 20 Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 0.2% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

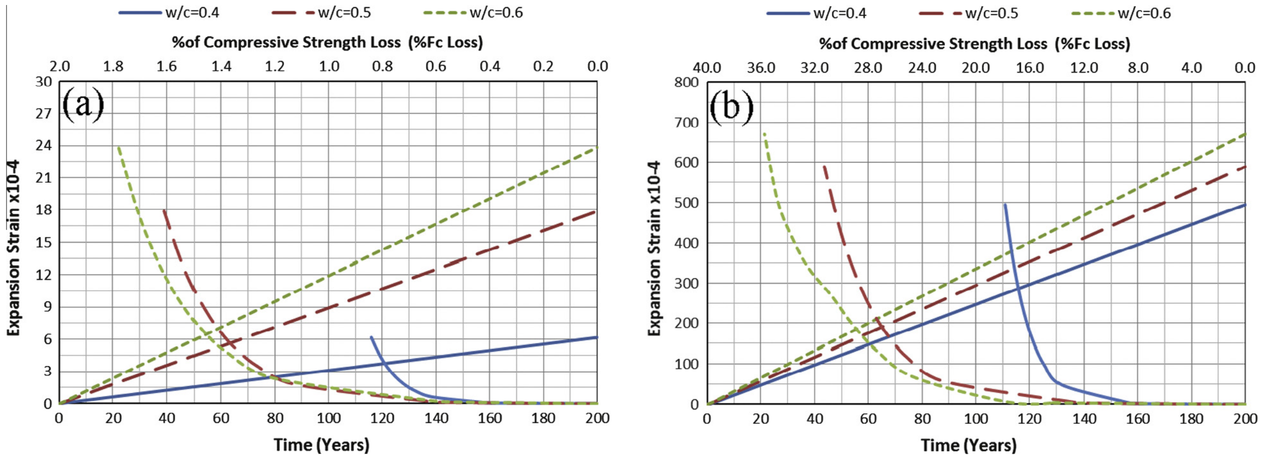

Figure 21 Prediction Of Expansion And Compressive Strength Loss vs. Time At 350 kg/M3 Cement Content Subjected To 0.2% Mg^{2+} Sulfate Ions (A) 0.2% C3A. (B) 9.0% C3A.

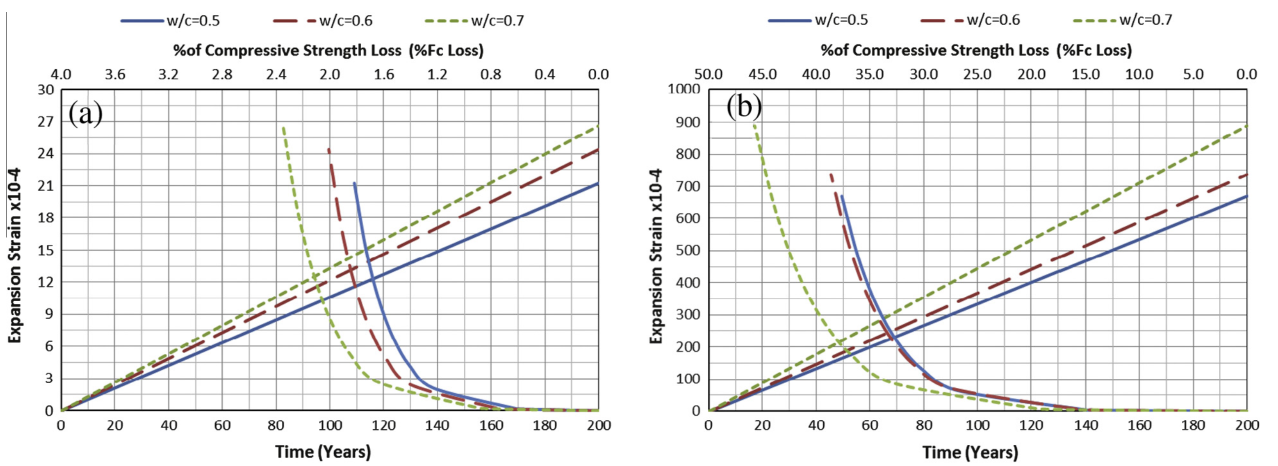

Figure 22 Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 0.2% Mg^{2+} sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

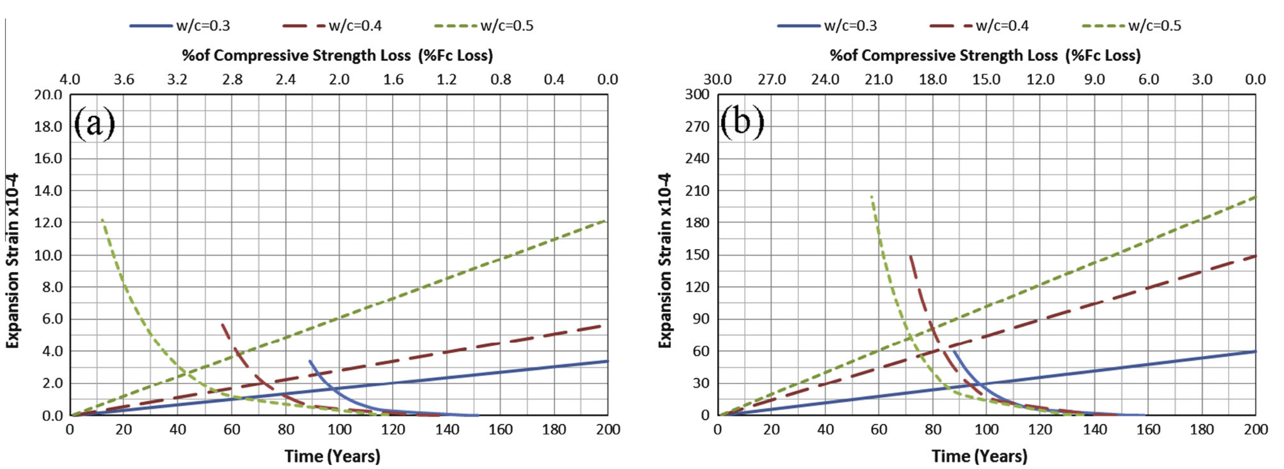

Figure 23 Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 1.0% Na^+ sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

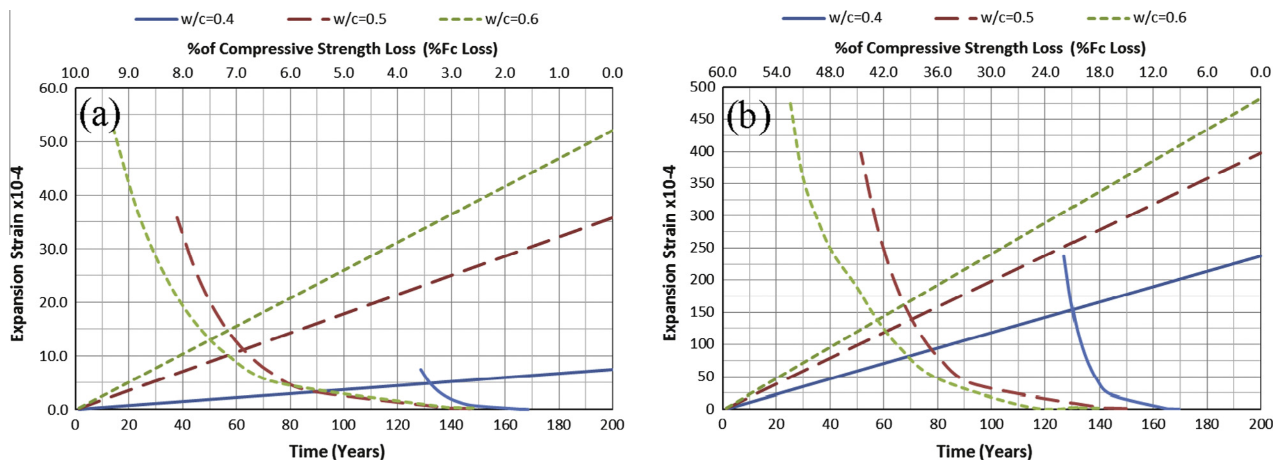

Figure 24 Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 1.0% Na^+ sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

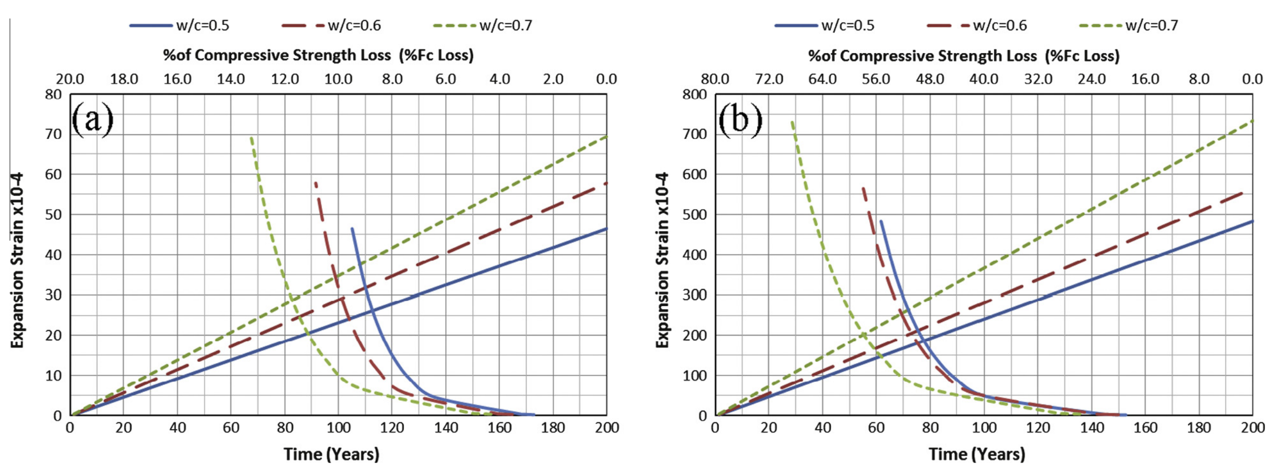

Figure 25 Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 1.0% Na^+ sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

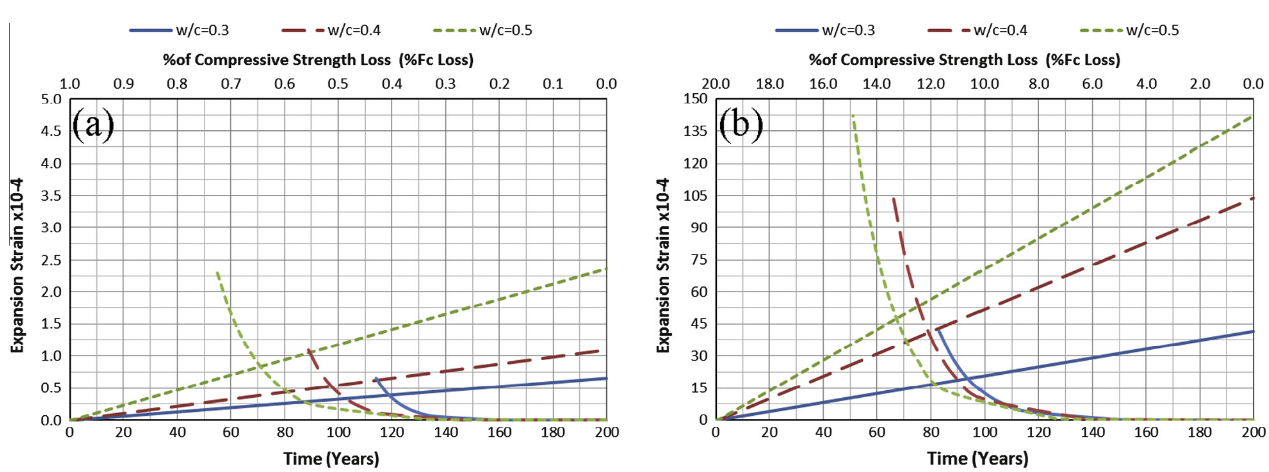

Figure 26 Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 0.2% Na^+ sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

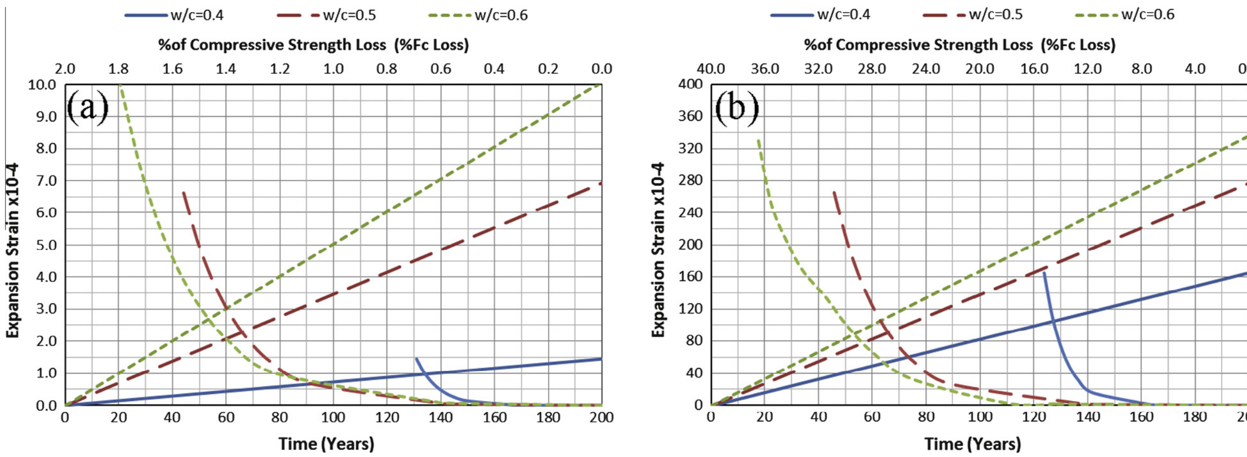

Figure 27 Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 0.2% Na^+ sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

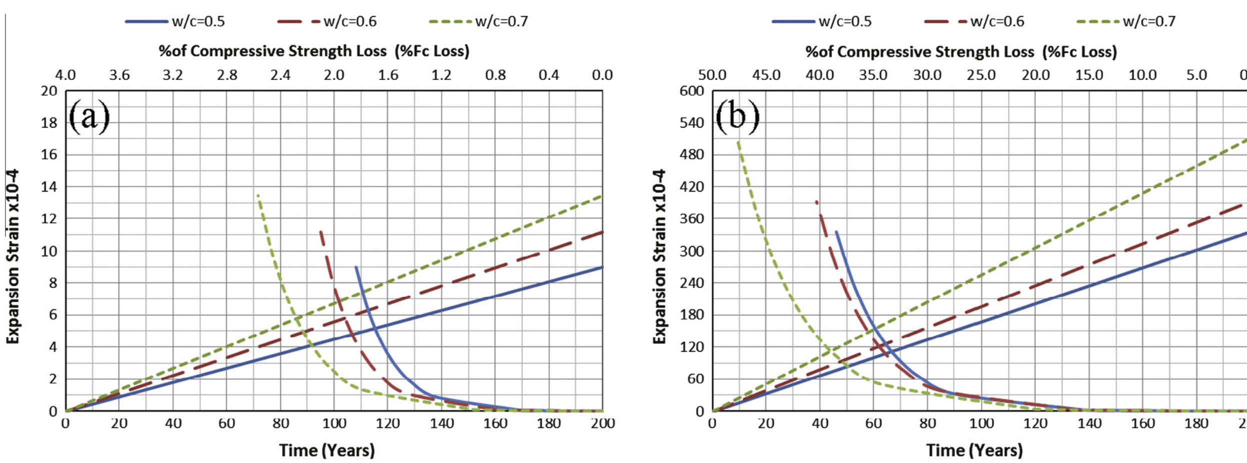

Figure 28 Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 0.2% Na^+ sulfate ions (a) 0.2% C_3A. (b) 9.0% C_3A.

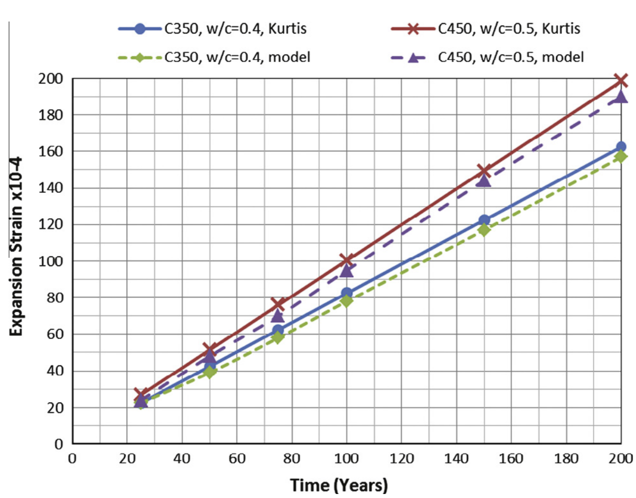

Figure 29 Comparison between models for expansion–time relation subjected to 2.1% Na^+ sulfate ions at 5.0% C_3A.

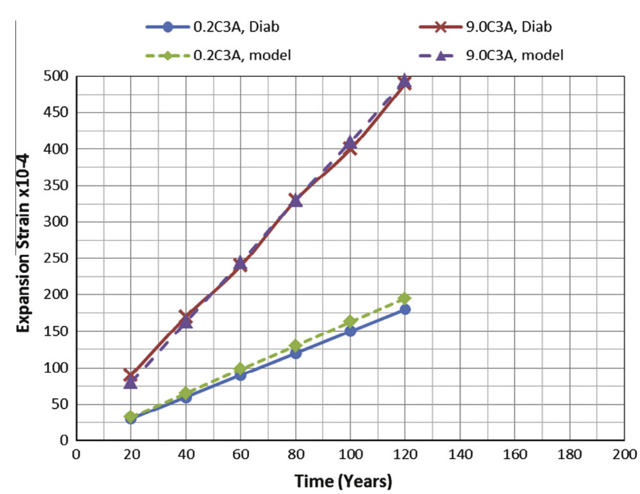

Figure 30 Comparison between models for expansion–time relation subjected to 5.0% Mg^{2+} sulfate ions at 0.5 w/c and 450 kg/m^{3}cement content.

These charts emphasize the importance of using low w/c ratio and low C_3A content to increase the sulfate resistance of concrete. In addition, the use of concrete with high cement content enhances the resistance due to sulfate attack. The effect of cement content is neglected in ACI code for concrete subjected to sulfate attack. These design charts can be used also to assess the alternative mix characteristics: w/c ratio, cement content, and C_3A content which add the same ability to resist sulfate attack.

6.2. Comparison between the proposed model and other models

The model may be compared with similar models that were presented in other published papers to ensure its reliability. Fig. 29 shows the comparison between predicted expansion by neural network model and Kurtis et al. [39] equation for 2.1% sodium sulfate attack. This figure shows high convergence between neural network model and Kurtis et al. [39].

Fig. 30 shows the comparison between predicted expansion by neural model and Diab et al. regression model for 5.0% magnesium sulfate attack. This figure shows high convergence between neural model and Diab et al. regression model with 450 kg/m^3 cement content and 0.5 w/c [21].

7. Conclusions

Based on the models presented previously, the following conclusions can be drawn:

(1) Numerical modeling using neural network shows a great performance to predict concrete properties subjected to sulfate attack where the minimum value of R^2 is 0.942 for testing set ANN.
(2) Design charts are established using neural network to predict the compressive strength loss due to sulfate attack for long time exposure.
(3) Design charts can be used easily to give different alternative mix constituents for concrete subjected to sulfate attack.
(4) Design charts emphasize the importance of using low w/c ratio and low C_3A content to increase the sulfate resistance of concrete. In addition, the use of concrete with high cement content enhances the resistance of concrete due to sulfate attack. However, ACI code for concrete subjected to sulfate attack neglects this effect.
(5) The comparison between the present model and other referenced models showed high convergence between neural network model and other models in predicting expansion.

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