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Comparison between Neural Network and Fuzzy Logic on Assessment of Long Term Concrete Compressive Strength and Expansion Due To Sulfate Attack

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Abstract—This study is divided into two phases. Phase I includes assessment of the validation of neural network and fuzzy logic in predicting mortar and concrete properties due to sulfate attack. These properties include expansion, weight loss, and compressive strength loss. The neural network and fuzzy logic models showed high validity on predicting compressive strength, expansion and weight loss for deteriorated concretes and mortars subjected to sodium and magnesium sulfate attack. The main objective of this study is presented in phase II. Phase II aims to present a new application of neural network to assess concrete compressive strength up to 200 years subjected to any concentration of sodium or magnesium sulfate. Cement content, water cement ratio, C3A content, and sulfate concentration were the inputs of the neural network model. Design charts were established using the output results of neural network models. These charts can be used easily to predict the compressive strength loss after any certain age and sulfate concentration for different concrete compositions.
Keywords—neural network, fuzzy logic, sulfate attack, compressive strength loss, interpolation

I. 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 exposure [1]. The reduction in compressive strength and expansion are 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 for short time nearly by 700 days [2,3]. The long term concrete properties needs more appropriate method [4]. Numerical modeling methods such as neural network and fuzzy logic are being increasingly used in civil engineering applications, especially for the purpose of interpolating the concrete properties [5,6,7].

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

More appropriates strategies for such cases derive as an approximating function that fits the shape or general trend of the data without necessarily matching the individual points.Artificial neural network and fuzzy logic arethe development of multiple regression methods. Although such approaches have commonsense 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, will be discussed in this paper.

II. NEURAL NETWORKS AND FUZZY LOGIC

Neural networks and fuzzy logic are the two most important concepts of artificial intelligence. They are useful in modeling or prediction of one or more variables, or simulation of a system.

A. 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,

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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].

B. Structural Applications Of Neural Network

In recent years ANN can 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 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]. Fatih Özcan et al [10] used neural networks to long-term compressive strength of silica fume concrete. Topcu [15] predicted properties of waste autoclaved aerated concreteaggregate concrete using artificial neural network.

Saridemir M et al [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 chlorides or sulfate attack was modeled by neural networks. Topçu 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] studied with the neural networkfor predicting compressive strength of concrete. Yaprak et al arranged the data used in the neural networkmodel 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.

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 et al [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.

C. Fuzzy Logic

Fuzzy logic (FL) is a way to make machines more intelligent. Fuzzy models use the probability to choose the way as humans do, and include verbal expressions instead of numbers. It is preferable when the mathematical problem is hard to derive, and when decisions have to be made with estimated values under incomplete information. First, it was proposed by Loutfi A. Zadeh in 1965 with the work “Fuzzy Set Theory” [17]. In 1974, E. H. Mamdani at the University of London published “Application to Control Problems” working on fuzzy logic. Later, this intelligence technique was applied in many areas [10]. The most successful areas of application are fuzzy control of physical or chemical parameters like temperature, electric current, flow of fluid, motion of machines etc. [17].

D. Structural Applications Of Fuzzy Logic

Fuzzy logic (FL) has been applied to many civil engineering problems which depend on logic relationships between different parameters. This method showed anintelligible degree of success in predicting outputs which related with inputs by obvious logic relations. Unal et al [17] studied with the fuzzy logic for predicting stress strain curves of fiber reinforced concrete.

Demir at al [18] was Modeling of some properties of the crushed tile concretes exposed to elevated temperatures. Uygunoglu et al [19] presented a fuzzy logic model for predicting the 28 day compressive strength under standard curing conditions. The input variables werew/c, fly ash content, and age.

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III. PROGRAM AND MODEL DEVELOPING

Concrete structures exposed to sulfates attack generally deteriorate due to formation of gypsum, and ettringite. This deterioration leads to decrease of compressive strength, weight loss, and volume increase (expansion) [20,21].

In this part, neural network and fuzzy logic model are developed to predict the concrete properties versus 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 and fuzzy logic system were collected from the experimental studies of many published papers [22-59].

A. Data Collecting And Grouping

The used data were collected from 38 different documented published papers [22-59]. Among of these, 2000 records were used for training, testing, and validating phases of neural network and fuzzy logic 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, C3A 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 were 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.

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, Fc_{int} (MPa)	16.5	78.4
Period of immersion (days)	7	16425
Output variables		
Compressive strength (MPa)	16.0	66.46
Expansion ($x10^{-4}$)	0.08	110
Weight loss (%)	0.074	6.30

TABLE 2: REFERENCES OF MORTAR AND CONCRETE DATA SET

Model No.	Data Set	Sulfate type	Output Variable	References Number
1-a	Concrete	Mg	Compressive strength	[22, 23, 24, 32, 34, 38, 56, 57]
1-b	Mortar	Mg	Compressive strength	[22, 23, 24, 29, 33, 46, 47, 58]
2-a	Concrete	Mg	Expansion	[22, 23, 24, 40, 56]
2-b	Mortar	Mg	Expansion	[22, 23, 24, 25, 44, 46]
3-a	Concrete	Mg	Weight loss	[22, 23, 24, 32]
3-b	Mortar	Mg	Weight loss	[22, 23, 24]
4-a	Concrete	Na	Compressive strength	[26, 32, 34, 37, 38, 39, 41, 45, 48, 50, 53, 55, 59]
4-b	Mortar	Na	Compressive strength	[29, 33, 39, 47, 49, 58]

5-a	Concrete	Na	Expansion	[26, 27, 28, 31, 35, 36, 37, 40, 41, 42, 43, 51, 53, 54]
5-b	Mortar	Na	Expansion	[25, 27, 30, 36, 44, 52]
6-a	Concrete	Na	Weight loss	[27, 32, 19]
6-b	Mortar	Na	Weight loss	[35]

B. Artificial Neural Network Architecture

Before model development proceeding, some model parameters were selected based on similar studies and the literature available [10,11,12].. The total database size in the present study was 2000 cases, considering 6 inputs and one output for each model. These data are divided to 80% for training, 10% for testing (also called verification) and 10% for validation according to Scbastia et al [10]. The preliminary architecture of the neural network according to MATLAB manual, see Fig 1 was conceived as follows:

1) *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) [10,11,12].
2) *Neurons In The First Layer:* Six neurons were specified using MATLAB manual according to model size.
3) *Hidden Layers:* It has been found that a single hidden layer presents satisfactory results for many problems [10].
4) *Neurons In Hidden Layer:* Eleven neurons were specified from empirical criteria [10].
5) *Number Of Outputs:* Single output in every model (compressive strength, expansion, weight loss).

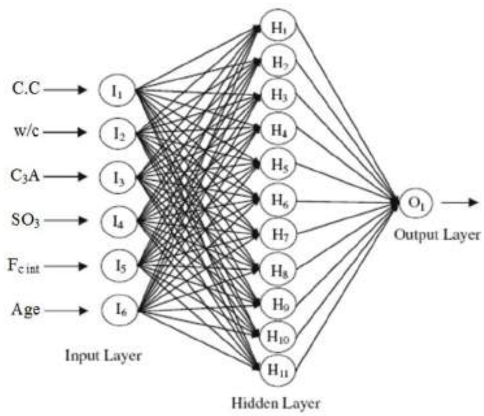

Fig 1. The chosen model architecture

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 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 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/or 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].

C. Fuzzy Logic Inference System

In this part of this study, the developed fuzzy logic based model was applied to predict the compressive strength, expansion, and weight loss data obtained from experiments. The fuzzy rules were written for this purpose based on algorithm model by using the fuzzy logic toolbox in MATLAB software. Totally, 2000 data experimental results were used in the processes of Mamdani-type fuzzy inference model in FL system. Of these, 80% of experiment results data were used for training, 10% for testing (also called verification) and 10% for validation [10]. The used FL model had six inputs parameters and one output parameters. The limit values of input and output variables used in Mamdani-type fuzzy interface model are listed in table 1.

In the rule base, fuzzy variables were connected with operators and the implication of each rule was calculated using weighted average defuzzification method. The membership functions of the training data set for the input variables of compressive strength, expansion %, and weight loss were determined of the triangular type and premise parameter sub-spaces [7].

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IV. RESULTS AND DISCUSSION

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

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2} \qquad Eq.1$$

$$R^2 = \frac{(n\sum t_i o_i - \sum t_i \sum o_i)^2}{\left(n\sum t_i^2 - (\sum t_i)^2\right)\left(n\sum o_i^2 - (\sum o_i)^2\right)} \qquad Eq.2$$

$$MAPE = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}|t_i - o_i|}{\sum_{i=1}^{n} t_i} x100\right] \qquad Eq.3$$

Where t is the target value, o is the output value, and n is the pattern. In the present study, compressive strength, expansion, and weight loss versus time due to sulfate attack were predicted using the multilayer feed-forward neural network and Mamdani-type fuzzy inference models. In the training and testing processes experimental data from thirty-eight different sources were used [22-59]. All results, obtained from experimental studies and the predicted values for compressive strength, expansion, and weight loss versus time are shown in Figs 2 to 7. From these figures, the values obtained from the training and testing using the ANN and FL models are very close to the experimental results. The results of ANN and FL models demonstrate that the ANN and FL systems 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 station for both ANN and FL models, are given in Table 3.

The best value obtained R^2 is 1.000 and 0.995 for training set ANN and FL, respectively while, the minimum value of R^2 is 0.942 and 0.823 for testing set ANN and FL, respectively. Comparison between ANN and FL in terms of R^2 is very difficult according to the convergence of R^2 values for both models. Although the values of R^2 are closed, the use of RMS, and MAPE statistical values show obviously the supremacy of ANN in the dispersion of predicted values. For instance, while the statistical value of R^2 in ANN and FL model No.1 is 0.999 and 0.985, respectively, the statistical value of RMS and MAPE from ANN is 0.003 and 0.002, respectively, and these values are 1.550 and 2.990 in FL models, respectively.

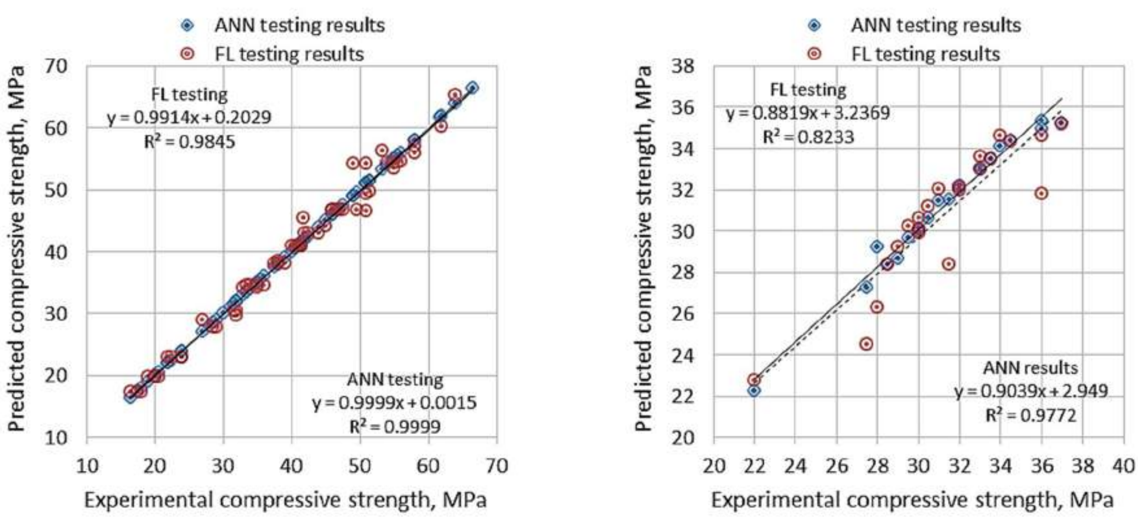

Fig 2. Model 1 predicted versus expreimental compressive strength for testing data (a- concrete, b- mortar) subjected to Mg2+ sulfate ions

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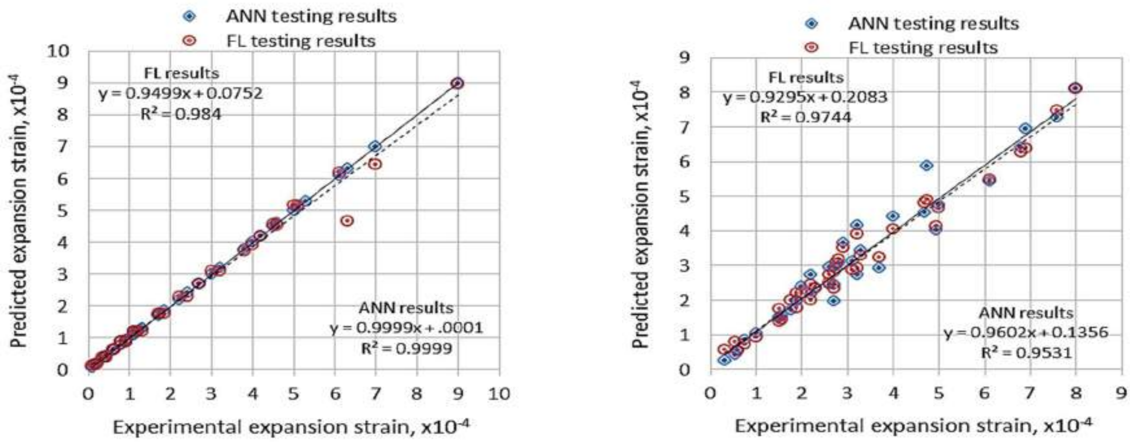

Fig 3. Model 2 predicted versus expreimental linear expansion for testing data (a- concrete, b- mortar) subjected to Mg2+ sulfate ions

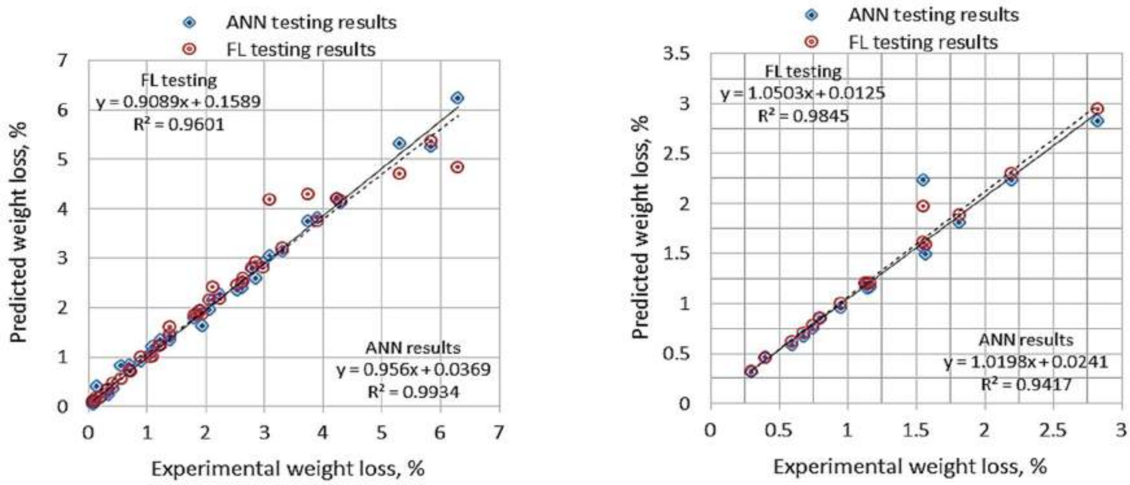

Fig 4. Model 3 predicted versus expreimental weight loss for testing data (a- concrete, b- mortar) subjected to Mg2+ sulfate ions

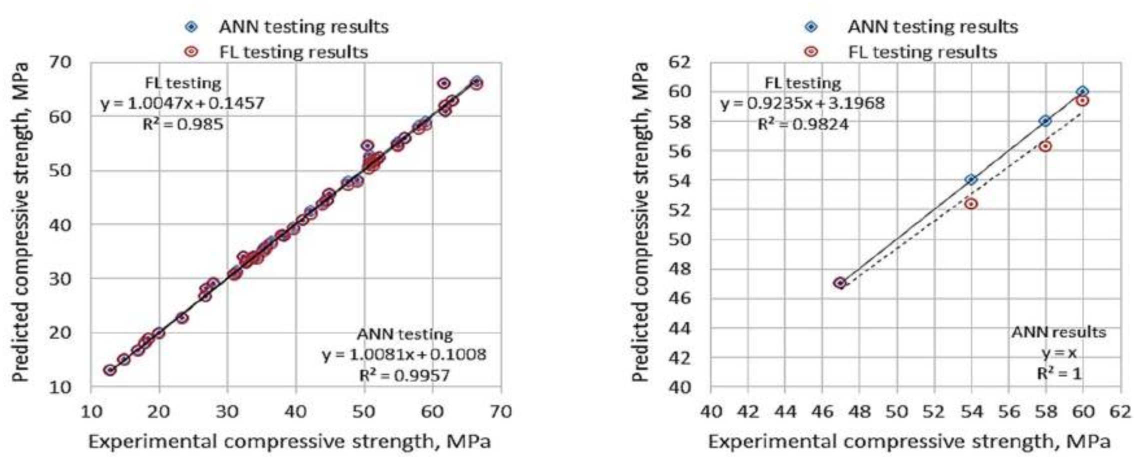

Fig 5. Model 4 predicted versus expreimental compressive strength for testing data (a- concrete, b- mortar) subjected to Na+ sulfate ions

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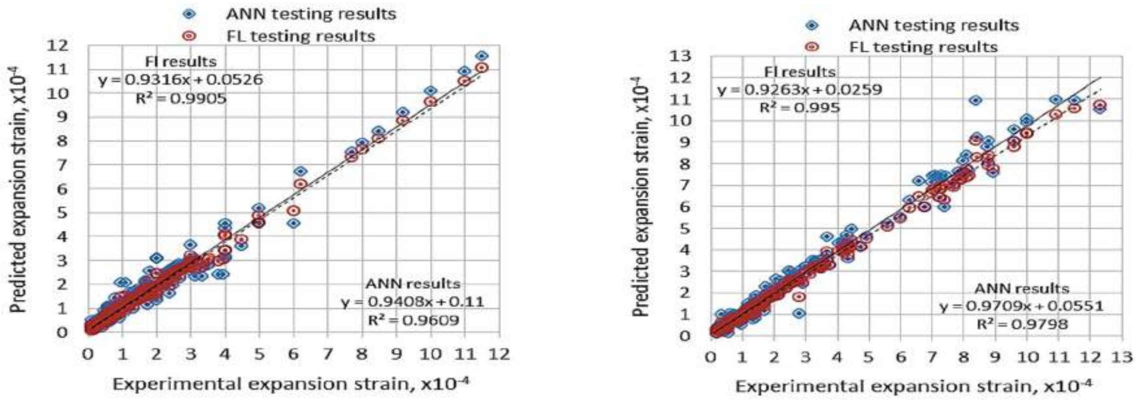


Fig 6. Model 5 predicted versus expreimental linear expansion for testing data (a- concrete, b- mortar) subjected to Na+ sulfate ions

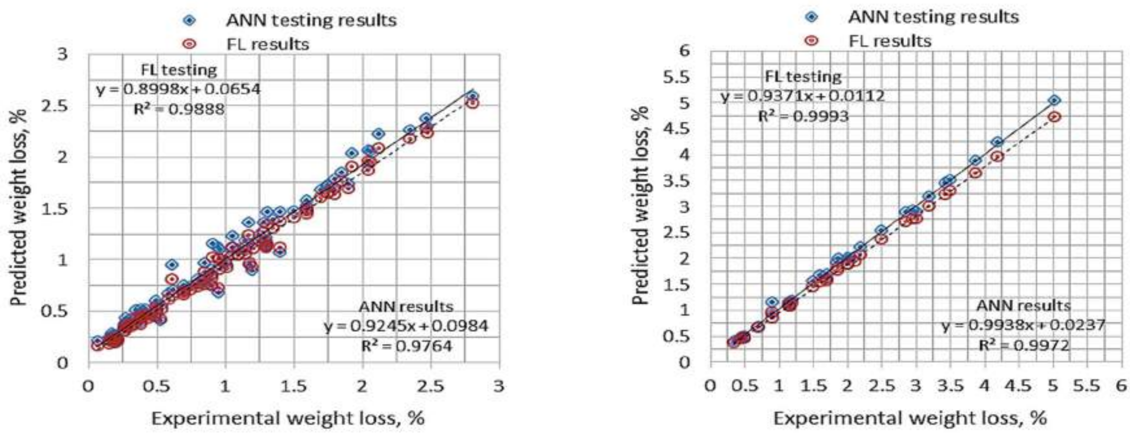


Fig 7. Model 6 predicted versus expreimental weight loss for testing data (a- concrete, b- mortar) subjected to Na+ sulfate ions

TABLE 3

THE STATISTICAL VALUES OF PROPOSED MODELS

Model No.	ANN			FL		
	RMS	R2	MAPE	RMS	R2	MAPE
1-a	0.003	0.999	0.002	1.550	0.985	2.990
1-b	0.560	0.977	1.040	1.480	0.823	3.060
2-a	0.001	0.999	0.010	0.300	0.984	7.020
2-b	0.425	0.953	10.00	0.326	0.974	11.72
3-a	0.150	0.993	13.57	0.330	0.960	7.370
3-b	0.174	0.942	5.360	0.119	0.985	6.180
4-a	0.970	0.996	1.120	1.003	0.985	1.400
4-b	0.000	1.000	0.000	1.230	0.982	1.750
5-a	0.350	0.961	24.42	0.210	0.991	11.70
5-b	0.396	0.980	16.86	0.327	0.995	9.900
6-a	0.116	0.976	16.34	0.105	0.988	11.17
6-b	0.064	0.997	3.530	0.190	0.993	5.880

V. 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 extracted from many published papers [22-59]. Neural network is used herein to predict this relation up to 200 years. Fuzzy logic models are excluded for this purpose. This exclusion is due to the accuracy of this method as mentioned previous. 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, C3A, 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 increases in one direction versus time where compressive strength values decreases as the time increases. Therefore, 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/m3cement and 5.0% C3A 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 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/m3 9.0% C3A and subjected to 5.0% Mg sulfate attack.

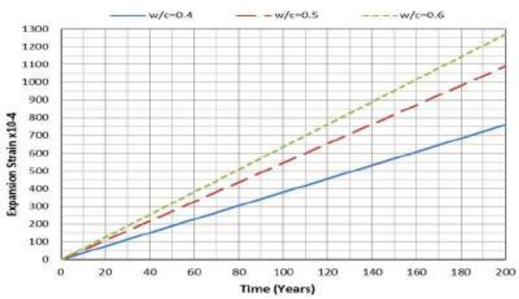


Fig 8. Prediction of expansion vs. time for 9.0% C_3A

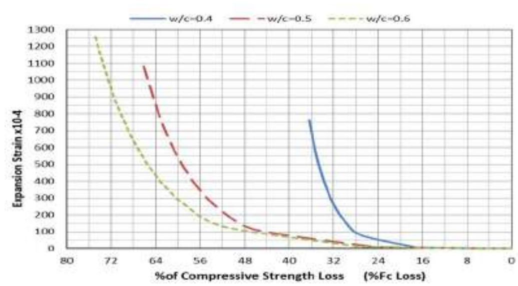


Fig 9. Prediction of compressive strength loss vs. expansion for 9.0% C_3A

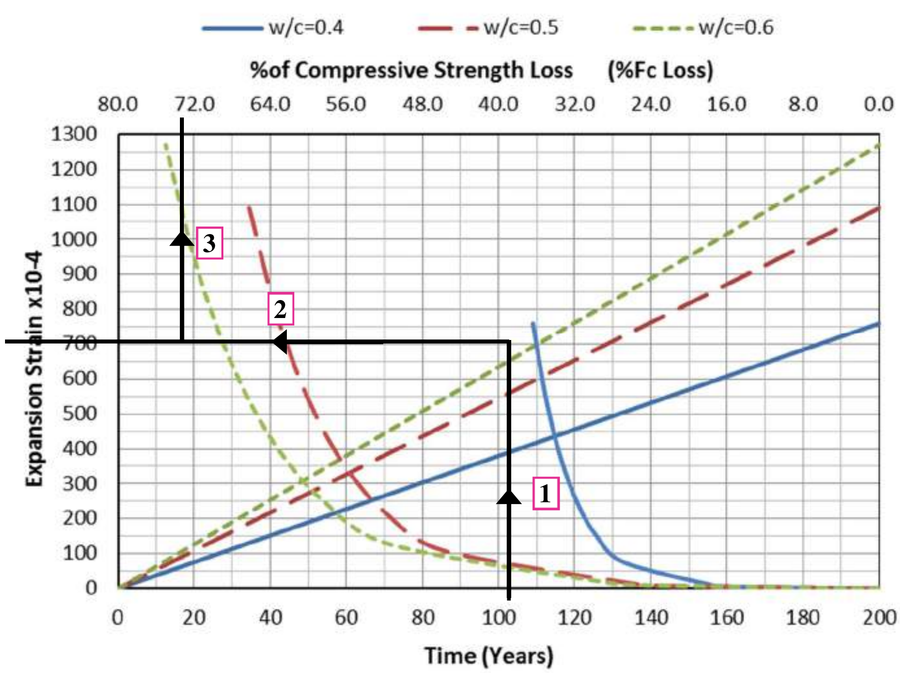


Fig 10. Expansion-time and expansion-compressive strength loss relation of concrete with 350 kg/m^3 cement content and 5.0%C_3A subjected to 5% Mg^{2+} sulfate ions

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:
Age 130 years.

Using the relation between expansion strain and age at 0.5 w/c ratio, expansion strain can be estimated as 700 x 10^{-4}.

Using an expansion of 700 x 10^{-4} and expansion-compressive strength loss relation. The expected compressive strength loss percentage can be estimated as 62%. These steps are summarized inn Fig 10.

A. 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 [60,61].
ACI 318 is divided into the sulfate attack to four zones according to the sulfate concentration and recommended a specified mix properties for each zone [60,61]. The proposed durability design charts can be expressed as the following items:
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).

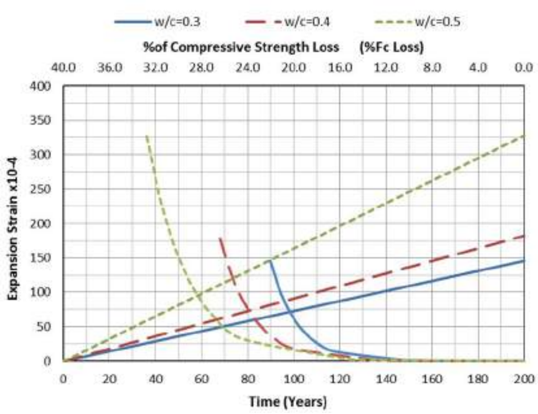
C_3A content. Four values are used as 0.2%, 2.0%, 5.0%, and 9.0%.

Sulfate concentration. SO_3 concentrations are specified as 0.2%, 1.0%, and 5.0%.

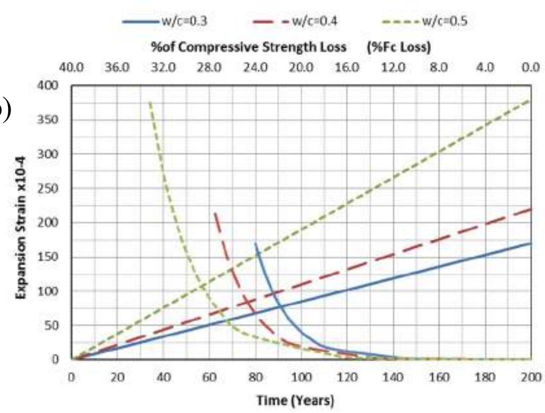
Type of ions. Sodium and magnesium sulfates are used.

Using the concept of neural network present in Fig 10, design charts for different parameter mention previously are constructed as shown in Figs 11 to 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/m3 while C_3A content varies between 0.2% and 9.0%. The effect of sulfate ions type is considered in these charts. The previous charts provides an easily 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 to 13). The compressive strength loss after 150 years is 16%, 31%, and 37% for cement content with 450, 350, and 300 kg/m3, respectively.
These charts emphasis the important 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. 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 having the same ability to resist sulfate attack.

(a)



(b)



(c) (d)

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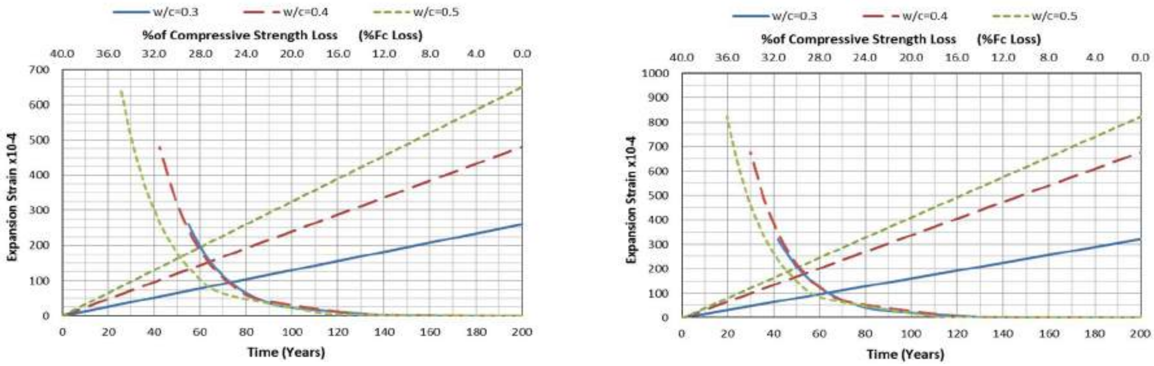


Fig11. Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 5% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)2.0%C_3A. (c)5.0%C_3A. (d)9.0%C_3A

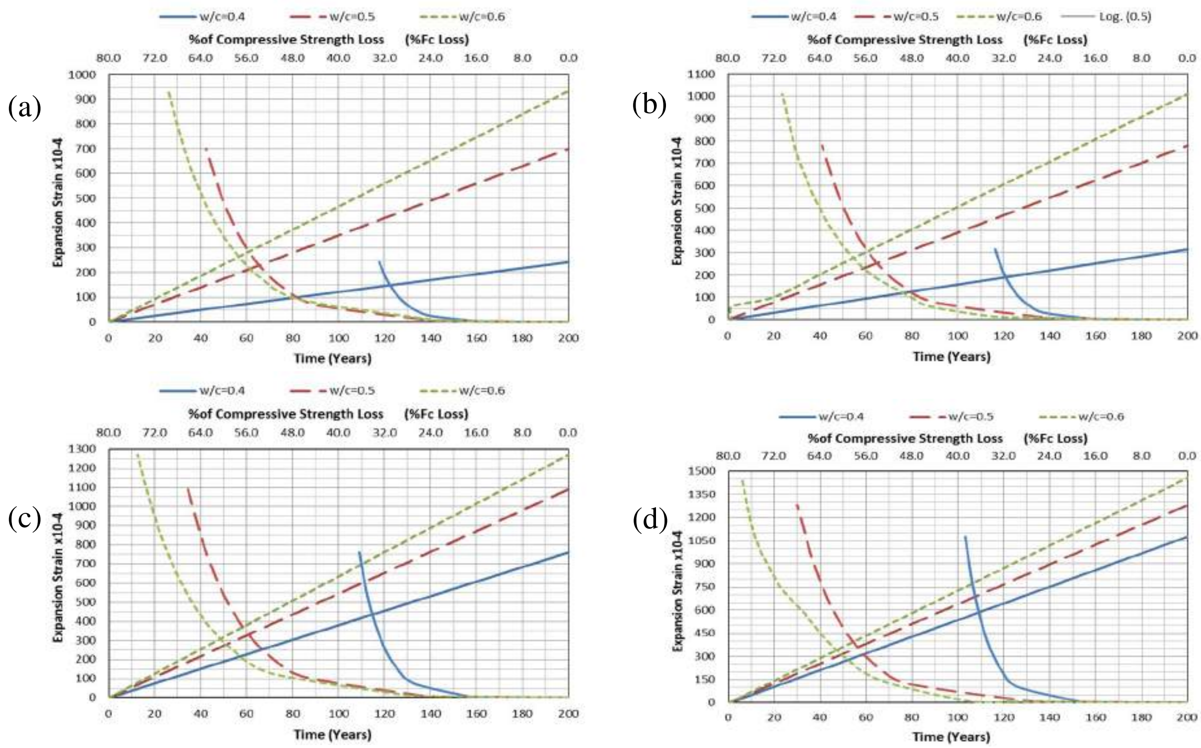
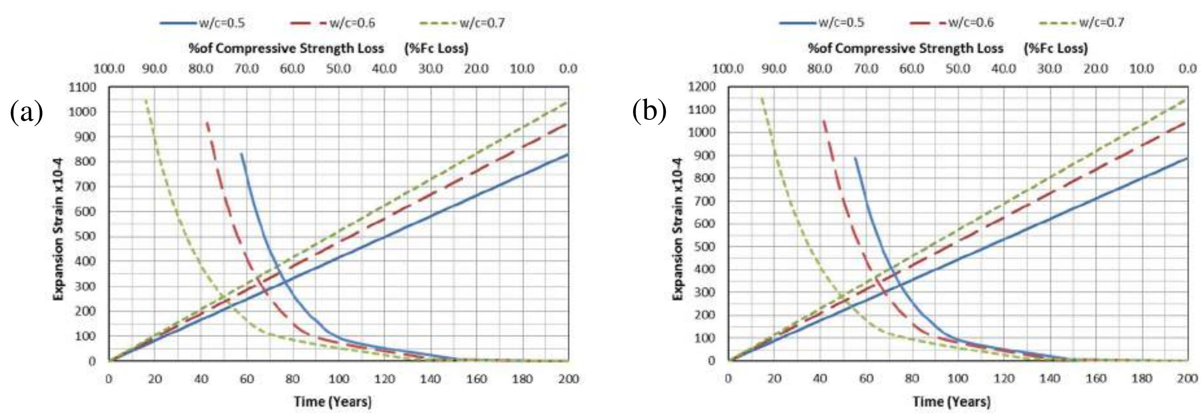


Fig12. Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 5% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)2.0%C_3A. (c)5.0%C_3A. (d)9.0%C_3A



 (c) (d)

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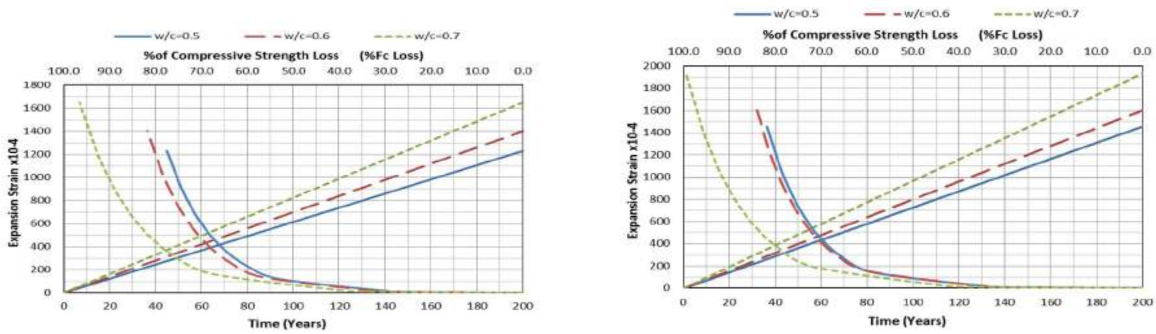


Fig13. Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 5% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)2.0%C_3A. (c)5.0%C_3A. (d)9.0%C_3A

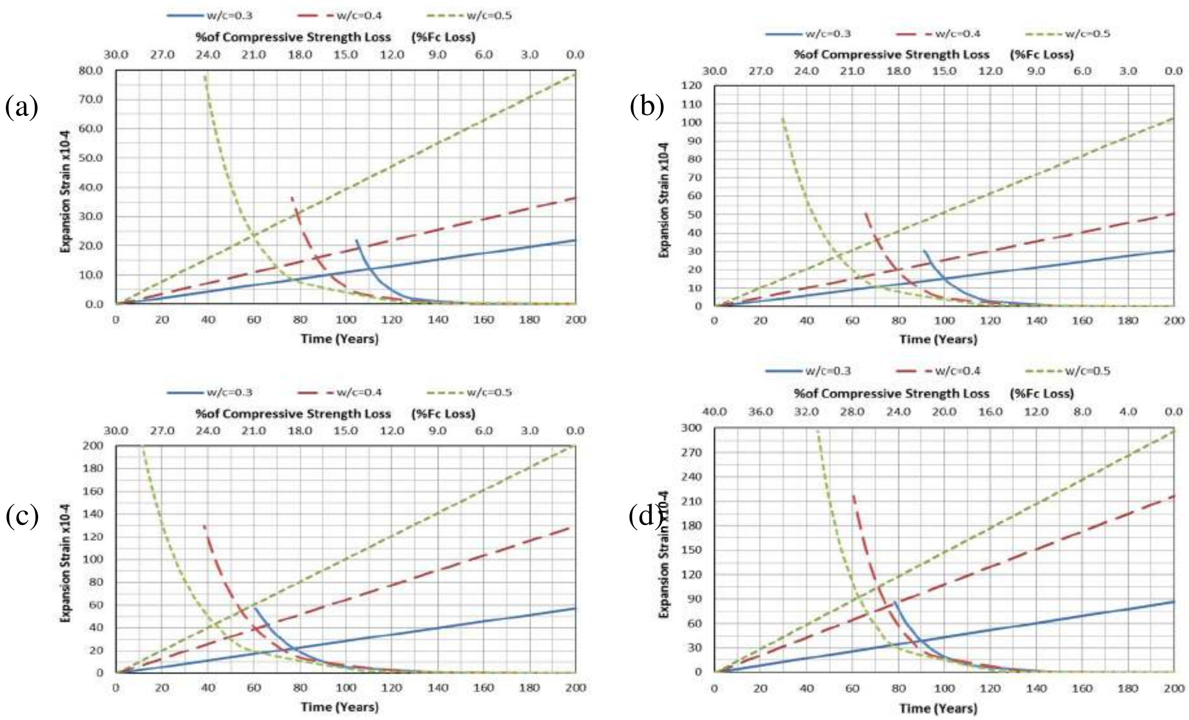
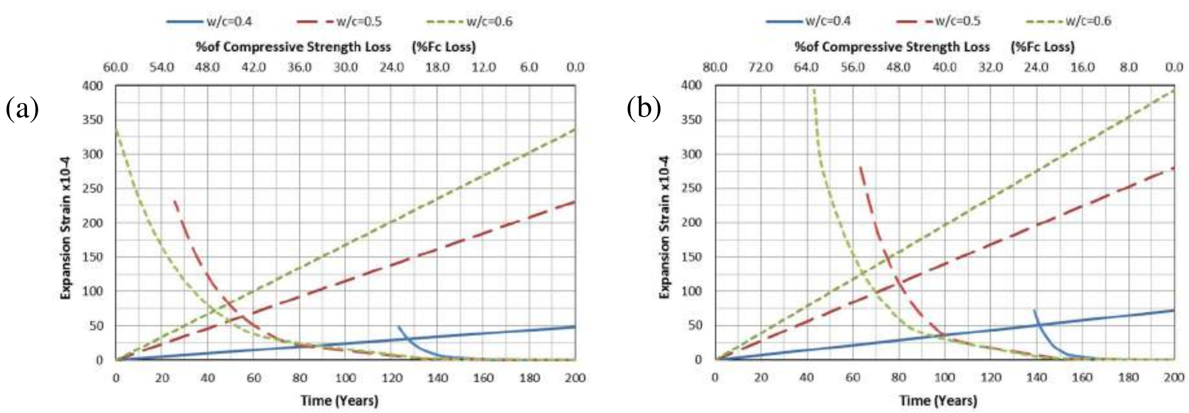


Fig14. Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 5% Na^+ sulfate ions (a)0.2%C_3A. (b)2.0%C_3A. (c)5.0%C_3A. (d)9.0%C_3A



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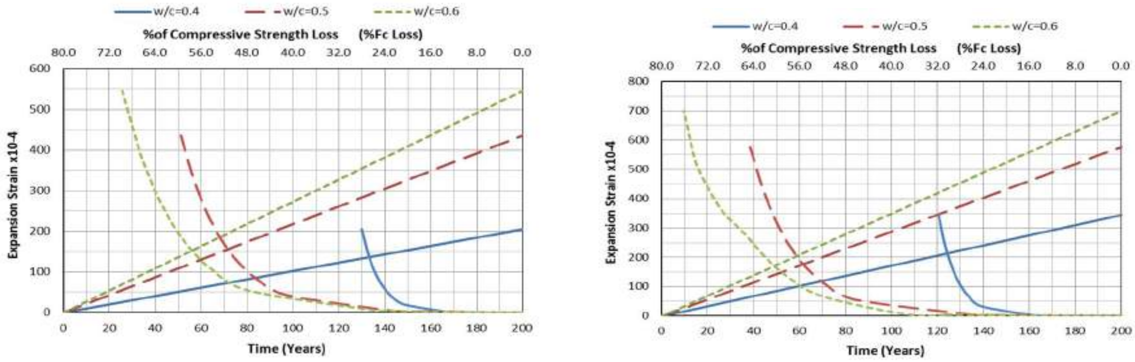

Fig15. Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 5% Na^+ sulfate ions (a)0.2%C_3A. (b)2.0%C_3A. (c)5.0%C_3A. (d)9.0%C_3A

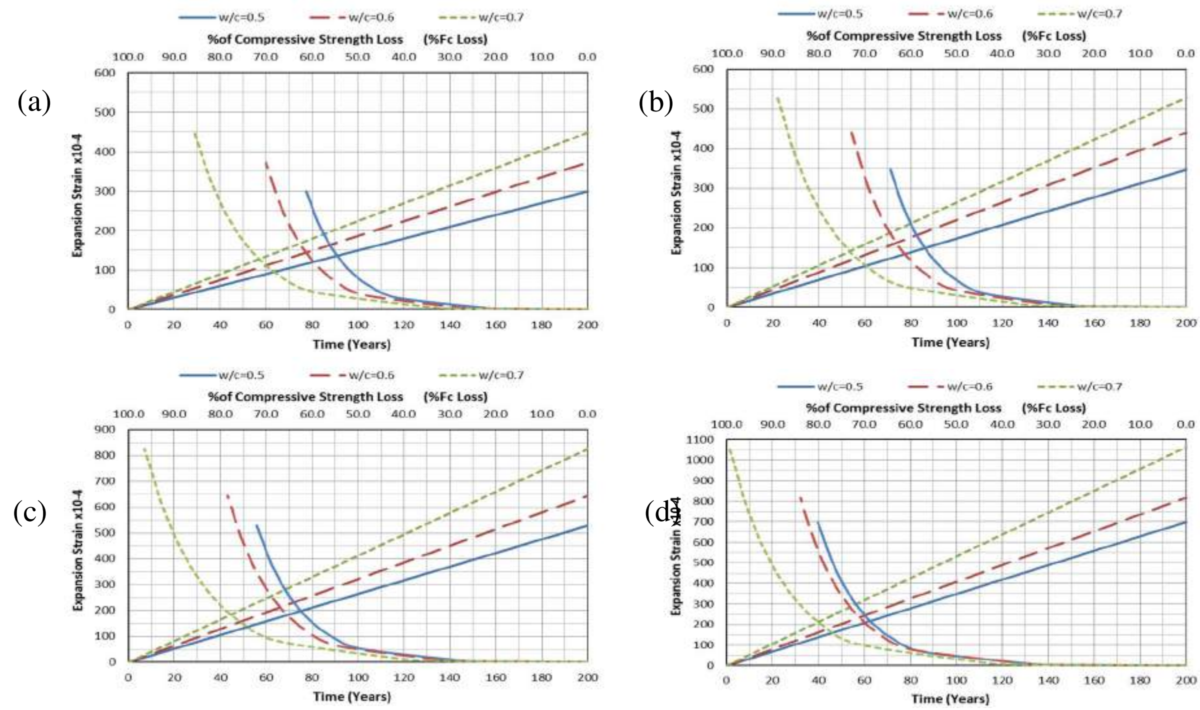

Fig 16. Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 5% Na^+ sulfate ions (a)0.2%C_3A. (b)2.0%C_3A. (c)5.0%C_3A. (d)9.0%C_3A

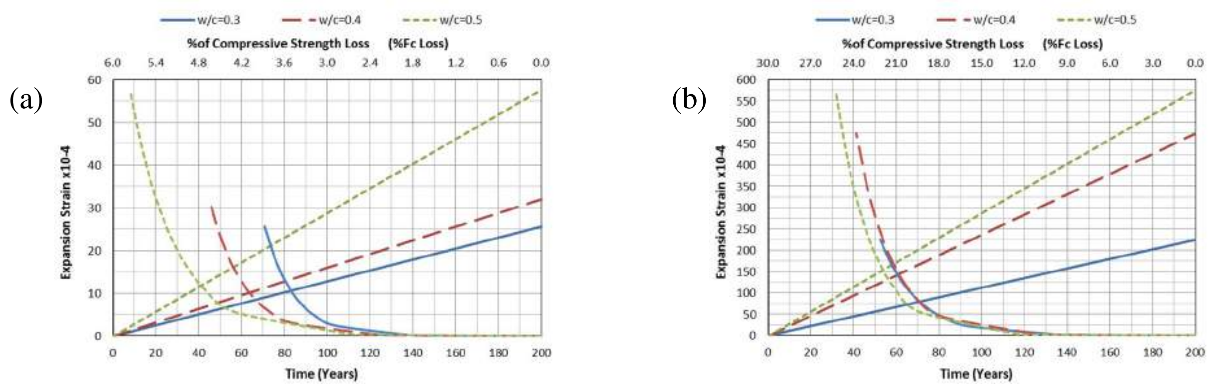

Fig17. Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 1.0% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

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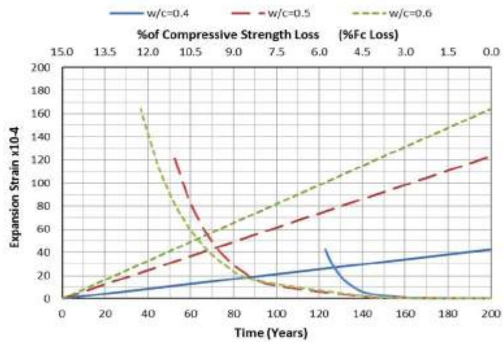
(a)


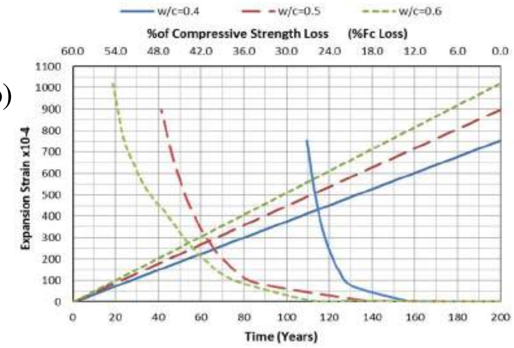
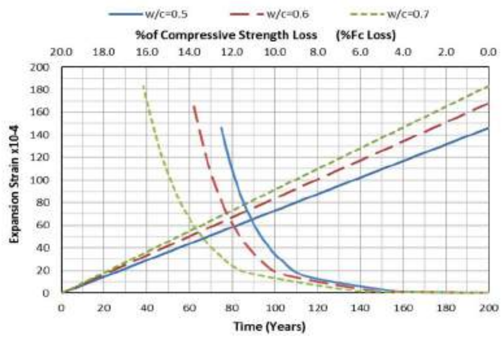
(b)


Fig18. 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

(a)


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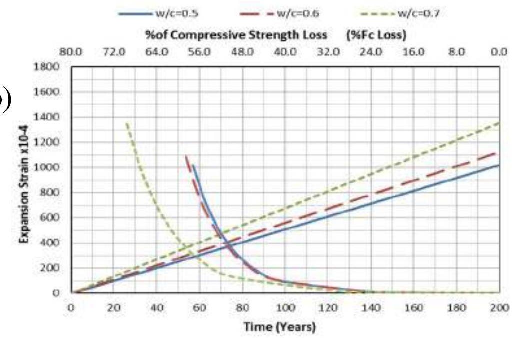
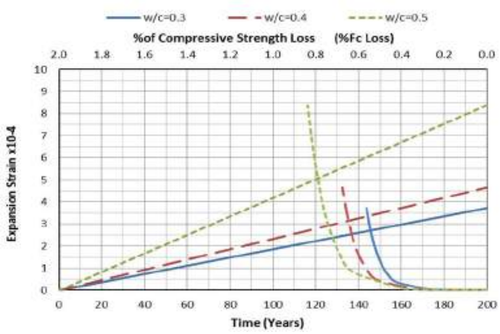


Fig19. Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 1.0% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

(a)


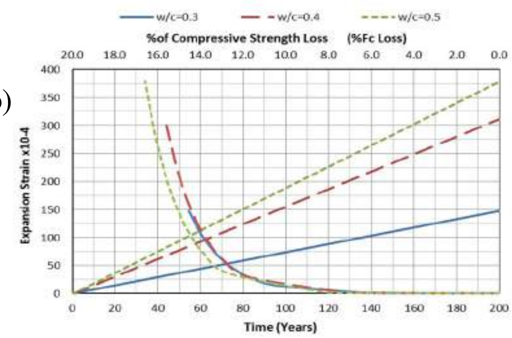
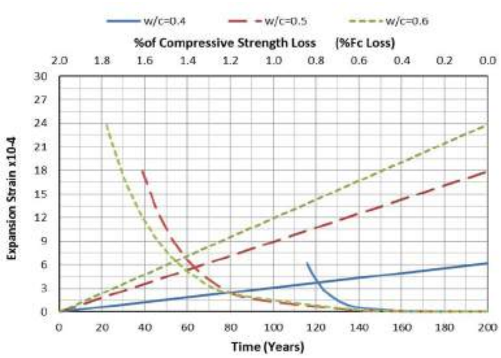
(b)


Fig 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

(a)


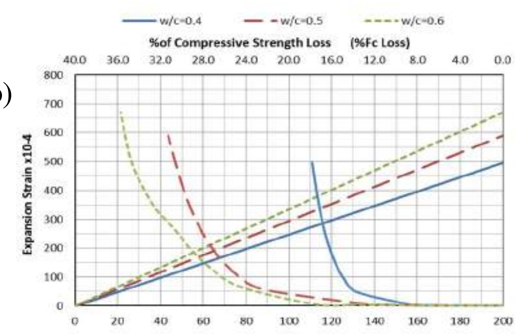
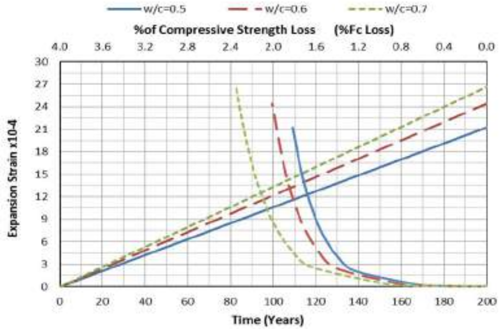
(b)


Fig 21. Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 0.2% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

(c)



(d)

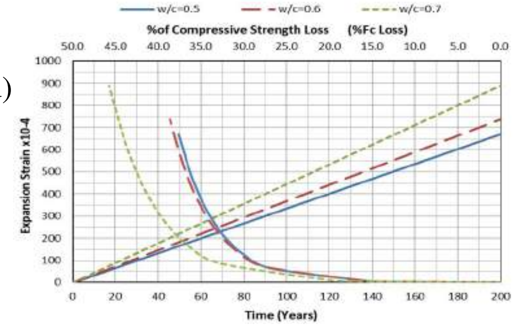
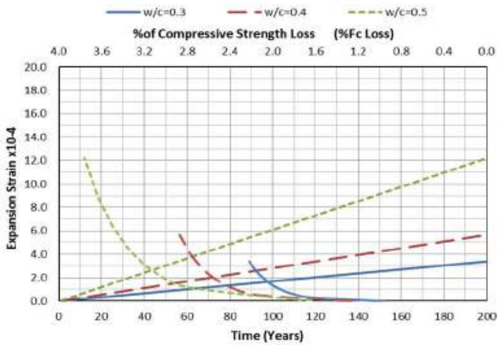


Fig22. Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 0.2% Mg^{2+} sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

(a)



(b)

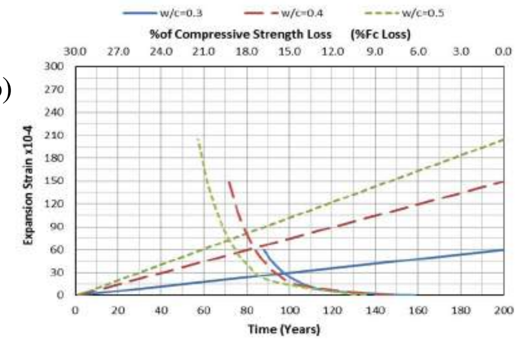
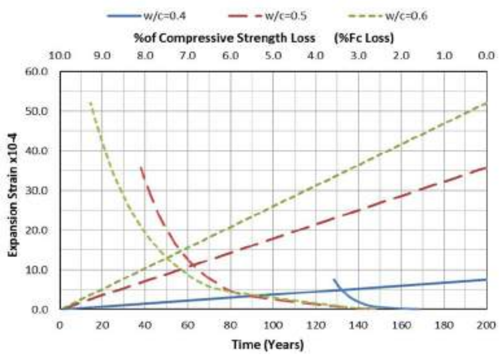


Fig23. Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 1.0% Na^+ sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

(a)



(b)

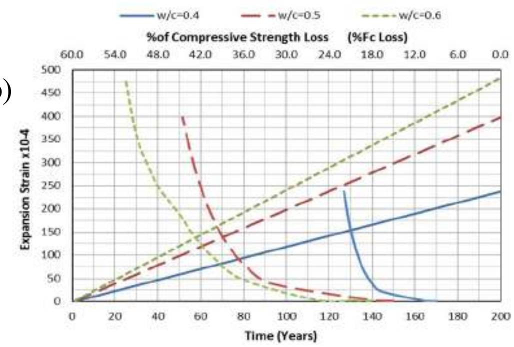
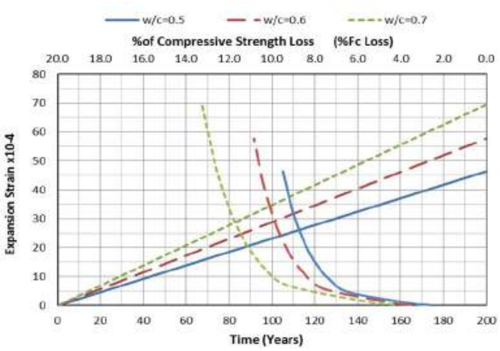


Fig24. Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 1.0% Na^+ sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

(a)



(b)

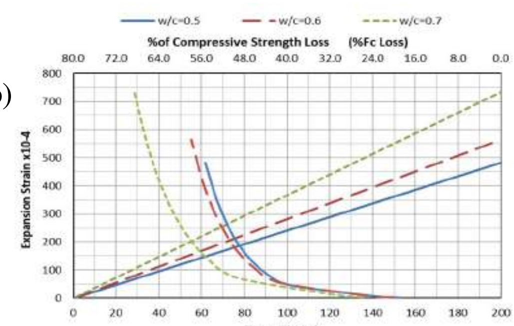


Fig25. Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 1.0% Na^+ sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

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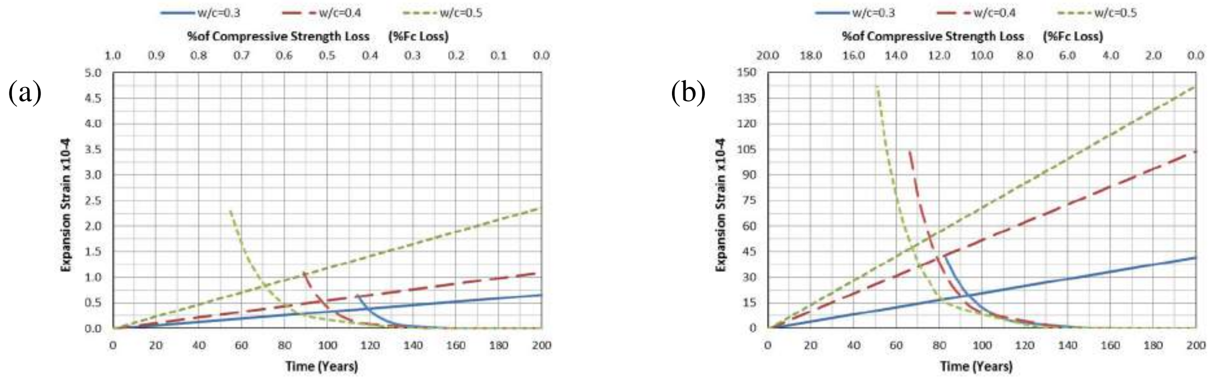

Fig26. Prediction of expansion and compressive strength loss vs. time at 450 kg/m^3 cement content subjected to 0.2% Na^+ sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

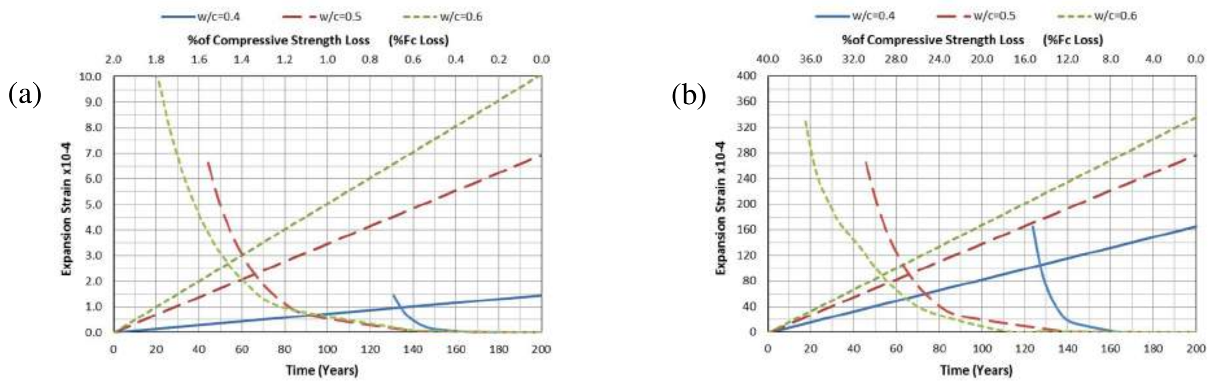

Fig27. Prediction of expansion and compressive strength loss vs. time at 350 kg/m^3 cement content subjected to 0.2% Na^+ sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

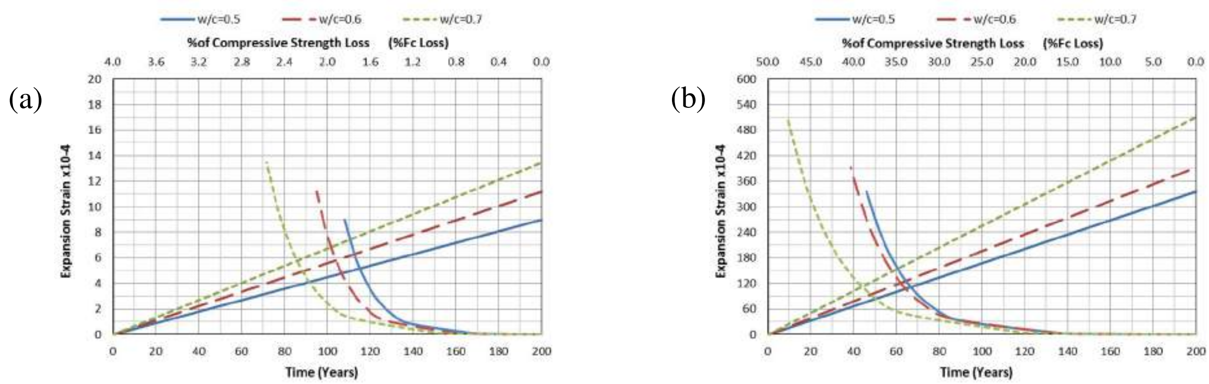

Fig28. Prediction of expansion and compressive strength loss vs. time at 300 kg/m^3 cement content subjected to 0.2% Na^+ sulfate ions (a)0.2%C_3A. (b)9.0%C_3A

B. 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 the reliability of this model. Fig 29 shows the comparison between predicted expansion by neural network model and Kurtis et al [42] equation for 2.1% sodium sulfate attack. This figure shows high convergence between neural network model and Kurtis et al [42]. Fig 30 shows the comparison between predicted expansion by neural model and Diab et al[24] regression model for 5.0% magnesium sulfate attack. This figure shows high convergence between neural model and Diab et al regression model with450 kg/m^{3}cement content and 0.5 w/c [24].

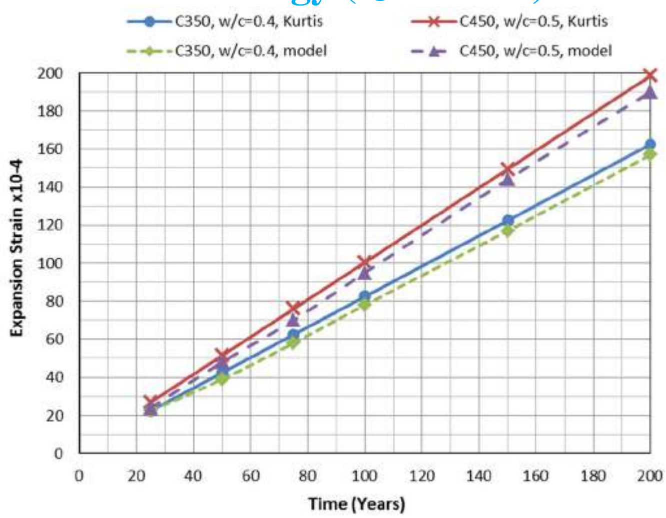

Fig 29. Comparison between models for expansion-time relation subjected to 2.1% Na^+ sulfate ions at 5.0%C_3A

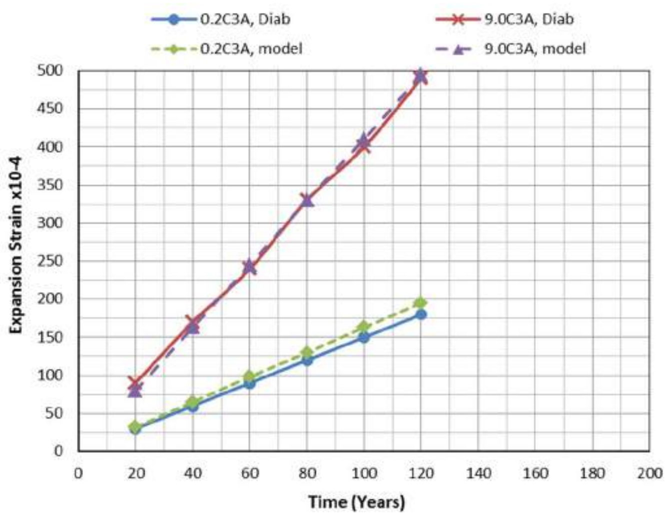

Fig 30. Comparison between models for expansion-time relation subjected to 5.0% Mg^{2+} sulfate ions at 0.5 w/c and 450 kg/m^3cement content

VI. CONCLUSION

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

Numerical modeling using neural network and fuzzy logic shows a great performance to predict concrete properties subjected to sulfate attack.

Neural network is more accurate compared with fuzzy logic in prediction of mortar and concrete properties due to sulfate attack.

Design charts are established using neural network to predict the compressive strength loss due to sulfate attack for long time exposure.

Design charts can be used easily to give different alternative mix constitutes for concrete subjected to sulfate attack.

The comparison between the present model and other referenced models showed high convergence between neural network model and other models in predicting expansion.

VII. ACKNOWLEDGMENT

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REFERENCES

[1] Neville A, The confused world of sulfate on concrete, Cement Concrete Res 2004; 34:1275-1296.
[2] Corr DJ, Monterio PJM, Kurits KE, and Kiureghian AD, Sulfate attack of concrete: Reliability analysis. ACI Mater J 2001; 98:99-104.
[3] Neville A, Neville on concrete. ACI, Farmington Hills. MI, USA, 2003.
[4] Cohen MD, and Mather B, Sulfate attack on concrete-Research needs, ACI Mater J 1991;38;62-69.
[5] Topcu IB, Boga AR, and Hocaoglu FO, Modeling corrosion currents of reinforced concrete using ANN. Automation in Const 2009; 18:145-152.
[6] Orejarena L, and Fall M, The use of artificial neural networks to predict the effect of sulfate attack on the strength of cemented paste backfill. Bull Eng Geol Environ 2010; 69:659-670.
[7] Saridemir M, Priction the compressive strength of mortars containing metakaolin by article neural networks and fuzzy logic. Advances in Eng Software 2009;40:920-927.
[8] Chapra SC, and Canale RP, Numerical methods for engineers. Fifth edition: 440-448.
[9] Chase W, and Bown F, General Statistics. Second edition: 496-500.
[10] Ozcan F, Atis CD, Karahan O, Uncuoglu E, and Tanyildizi H, Comparison of artificial neural network and fuzzy logic models for prediction of long term compressive strength of silica fume concrete, Advances in Eng Software 2009;40:856-863.
[11] Yaprak H, Karacı AI, and Demir II, Prediction of the effect of varying cure conditions and w/c ratio on the compressive strength of concrete using artificial neural networks, Neural Comput&Applic 2011.
[12] Dias WPS, and Pooliyadda SP, Neural networks for predicting properties of concretes with admixtures. Construction Building Mat 2001; 15:371-379.
[13] Goktepe AB, Inan G, ramyar K, and Sezer A, Estimation of sulfate expansion level of PC mortar using statistical and neural approaches. Construction Building Mat 2006; 20:441-449.
[14] Guneyisi E, Gesoglu M, Ozturan T, and Ozbay E, Estimation of chloride permeability of concretes by empirical modeling: Considering effect of cement type, curing condition and age. Construction Building Mat 2009; 23:469-481.
[15] Topcu IB, and Sarıdemir M, Prediction of properties of waste AAC aggregate concrete using artificial neural network. Computational Mat Science 2007; 41:117-125.
[16] Pann KS, Yen T, Tang CW, and Lin TD, New strength model based on water cement ratio and capillary porosity. ACI Mater J 2003; 100:311-317.
[17] Unal O, Demir F, and Uygunoglu T, Fuzzy logic approach to predict stress strain curves of steel fiber reinforced concretes in compression, Building and Enviro 2007; 42:3589-3595.
[18] Demir A, Topçu IB, and Kus H,Modeling of some properties of the crushed tile concretes exposedto elevated temperatures.Const and Build Mat;2011; 25:1883–1889.
[19] Uygunoglu T, and Unal O, A new approach to determination of compressive strength of fly ash concrete using fuzzy logic. Journal of Scientific & Industrial Research 2006; 65:894-899.
[20] Santhanam M, Cohen MD, and Olek J, Mechanism of sulfate attack: a fresh look Part 2. Proposed mechanisms, Cement Concrete Res 2003; 33:341-346.
[21] Femy C, and Taylor FW, Ettringite in hydration of Portland cement concrete and its occurrence in Mature Concrete. ACI Mater J 2001; 98:350-355.
[22] Diab AM, Abdelwahab AM, Elyamany HE, and Abdelmoty AM. Blended cement is a bad recommendation for magnesium sulfate attack. International Conference On Microstructure Related Durability of Cementitious Composites held in Nanjing, China; 2008.
[23] Diab AM, Abdelwahab AM, Elyamany HE, and Abdelmoty AM, Magnesium sulfate resistance of concrete of silica fume concrete specimens and R.C columns, International Conference On Microstructure Related Durability Of Cementitious Composites held in Nanjing, China; 2008.
[24] Diab AM, Abdelwahab AM, Elyamany HE, and Abdelmoty AM, Guidelines in compressive strength assessment of concrete modified with silica fume due to magnesium sulfate attack. Construction Building Mat 2012; 36:311-318.
[25] AL-Amoudi OSB, Maslehuddin M, and Saadi MM, Effect of magnesium sulfate and sodium sulfate on the durability performance of plain blended cement. ACI Mater J 1995; 92:15-23.
[26] Ghafoori N, and Zhang Z, Sulfate Resistance of Roller-Compacted Concrete. ACI Mater J 1998; 95:347-355.
[27] Stephens JB, and Carrasquillo RL, Evaluating performance-based test and specifications for sulfate resistance in concrete. Research Project 0-1706. Texas department of transportation; 1999.
[28] Bassuoni MT, and Nehdi ML, Durability of self-consolidating concrete to sulfate attack under combined cyclic environments and flexural loading. Cement Concrete Res 2007; 39:206-226.
[29] Seung TL, Hooton RD, Jung HS, Park DH, and Chang SC, Effect of limestone filler on the deterioration of mortars and pastes expose to sulfate solutions at ambient temperature. Cement Concrete Res 2008; 38:68–76.
[30] Tikalsky PJ, Roy D, Scheetz B, and Krize T, Redefining cement characteristics for sulfate-resistant Portland cement. Cement Concrete Res 2002; 32:1239-1246.
[31] Ghafoori N, Diawara H, and Beasley S, Resistance to external sodium sulfate attack for early-opening-to-traffic Portland cement concrete. Cement Concrete Composites 2008; 30:444–454.
[32] Park YS, Suh JK, Lee JH, and Shin YS, Strength deterioration of high strength concrete in sulfate environment. Cement Concrete Res 1999; 29:1397–1402.
[33] Lee ST, Moon HY, and Swamy RN, Sulfate attack and role of silica fume in resisting strength loss. Cement Concrete Composites 2005; 27:65–76.
[34] Turkmen I, Influence of different curing conditions on the physical and mechanical properties of concretes with admixtures of silica fume and blast furnace slag. Materials Letters 2003; 57:4560–4569.
[35] Al-Akhras NM, Durability of metakaolin concrete to sulfate attack. Cement Concrete Res 2006; 36:1727–1734.

[36] Rozière E, Loukili A, El Hachem R, and Grondin F, Durability of concrete exposed to leaching and external sulphate attacks. Cement Concrete Res 2009; 39:1188–1198.
[37] Najimi M, Sobhani J, Pourkhorshidi AR, Durability of copper slag contained concrete exposed to sulfate attack. Construction Building Mat 2011; 25:1895–1905.
[38] Sumer M, Compressive strength and sulfate resistance properties of concretes containing Class F and Class C fly ashes. Construction Building Mat 2012; 34:531–536.
[39] Vu DD, Stroeven P, and Bui VB, Strength and durability aspects of calcined Kaolin-blended Portland cement mortar and concrete. Cement Concrete Composites 2001; 23:471–478.
[40] Zhang M, Chen J, Yunfeng L, Wang D, Jian Y, Study on the expansion of concrete under attack of sulfate and sulfate–chloride ions. Construction Building Mat 2012:in press.
[41] Wee TH, , Suryavanshi AK, Wong SF, and Rahman AKM, Sulfate resistance of concrete containing mineral admixtures. ACI Mater J 2000; 97:536-549.
[42] Kurtis KE, Monterrio PJM, and Madant SM, Empirical models to predict concrete expansion caused by sulfate attack, ACI Mater J 2000;97:456-161.
[43] Haj-Ali Rm, Kurtis KE, and Sthapit AR, Neural network modeling of concrete expansion during long-term sulfate exposure, ACI Mater J 2001;98:36-43.
[44] Inan G, Goktepe AB, Ramyar K, and Sezer A, Prediction of sulfate expansion of PC mortar using neuro-fuzzy methodology, Building and Enviro 2007;42:1264-1269.
[45] Shanahan N, and Zayed A, Cement composition and sulfate attack Part I. Cement Concrete Res 2007; 37:618–623.
[46] Zeli J, Radovanovi I, and Jozi D, The effect of silica fume additions on the durability of Portland cement mortars exposed to magnesium sulfate attack, Mat and tech 2007;41:91–94.
[47] Cohen MD, and Bentur A, Durability of Portland cement-silica fume pastes in magnesium sulfate and sodium sulfate solutions, ACI Mat J 1987;139-157.
[48] Tikalsky PJ, and Carrasquiilo RL, Influence of fly ash on the sulfate resistance of concrete, ACI Mat J 1992; 89:69-75.
[49] Irassar EF, Gonzalez M, and Rahhal V, Sulfate resistance of type V cements with limestone filler and natural pozzolana. Cem. Concr. Compos 2000; 22:361-368.
[50] Stark D, Durability of concrete in sulfate-rich soils. Research and Development Bulletin, vol. RD O97, Portland Cement Assn, Skokie, IL, 1989.
[51] Stark D, Performance of concrete in sulfate environments. Research and Development Bulletin, vol. RD 129, Portland Cement Assn, Skokie, IL, 2002.
[52] Brown PW, An evaluation of the sulfate resistance of cements, Cem Concr Res 1981; 11:719–727.
[53] Schneider U, Piasta WG, The behavior of concrete under Na2SO4 solution attack and sustained compression or bending. Mag Concr Res 1991; 43:281-289.
[54] U.S Department of the Interior, Bureau of Reclamation, USBR 4908: Procedure for length change of hardened concrete exposed to alkali sulfates. Concrete Manual 1980; 2:680-684.
[55] Atkinson A, and Hearne JA, Mechanistic model for the durability of concrete barriers exposed to sulfate bearing groundwater, mater Res. Soc. Symp. Proc. 1990; 176:149-156.
[56] Sanathanam M, Studies on sulfate attack: Mechanisms, Test methods, and Modeling, PhD Thesis, Purdue University, August 2001.
[57] Inse R, Prediction of fracture parameters of concrete by artificial neural networks. EngFractMech 2004; 71(15):2143-59.
[58] Bescop PL, and Solet C, External sulfate attack by ground water. Experimental study on CEM I cmenet paste. Renvue Europe enne de Genie civil 10:2006; 10:1127-1145.
[59] Glasser FP, Marchand J, and Samson E, Durability of concrete – degredation phenomena involving detrimental chemical reactions. Cement Concr. Es. 2008; 38:226-246.
[60] ACI Committee 201-2R-1, Guide to Durable Concrete. American Concrete Institute; 2009.
[61] ACI Committee 318, Building Code Requirements for Structural Concrete and Commentary. American Concrete Institute; 2008.