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Research paper

Implementation of Artificial Neural Networks for Prediction of Chloride Penetration in Concrete

Osama Ahmed Mohamed [1], Modafar Ati [2], Waddah Al Hawat [3]

[1]*Civil Engineering Department, College of Engineering, Abu Dhabi University, United Arab Emirates*
[2]*Computer Science & Information Technology Department, College of Engineering, Abu Dhabi University, United Arab Emirates*
[3]*Civil Engineering Department, College of Engineering, Abu Dhabi University, United Arab Emirates*
**Corresponding author E-mail: modafar.ati@adu.ac.ae*

Abstract

Artificial Neural Networks (ANN) has received a great attention from researchers in previous decade to predict different aspect of engineering problems. The aim of this research is to present an implementation of ANN to predict the Chloride penetration of self-consolidating concrete (SCC), containing various amounts of cement replacement minerals including fly ash, silica fume, and slag. The ability of concrete to resist chloride penetration is measured using Rapid Chloride Penetration (RCP) test through an experimental program. One- and two-layer ANN models were developed by controlling the critical parameters affecting chloride penetration to predict the results of RCP test. The ANN models were developed using various parameters including ratio of water-to-binder (w/b), course aggregate, fine aggregate, fly ash, and silica fume. It was shown that the prediction accuracy of ANN models was sensitive to combinations of learning rate and momentum. Data used to train and test the ANN were obtained through an experimental program conducted by the authors.

Keywords: *artificial neural network, Chloride penetration, fly ash, self-consolidating concrete, silica fume, slag.*

1. Introduction

Concrete in marine environmental or in soils containing appreciable levels of chlorides is susceptible to damage, particularly pursuant to corrosion of reinforcing steel. As part of on-going study to develop sustainable self-consolidating concrete, chloride penetration resistance of samples obtained from several mixes was determined using the RCP Test, in accordance with ASTM C1202. ANN models were developed to predict chloride penetration levels in concrete where the cement was partially replaced with various amounts of minerals including fly ash, silica fume, and slag as demonstrated in this paper. Experimental data on the influence of fly ash and basalt fibers on strength and chloride penetration resistance of SCC was presented by Mohamed and Al-Hawat [1]. Mechanical properties of SCC examined in this study, such as splitting tensile strength, were reported by Mohamed and Najm [2] and Mohamed et al. [3].

due to the fact that ANN has the ability to handle complex data has contributed to the increase of its popularity. Furthermore, the rapid increase of computation power in recent years has added another factor to use the ANN in different fields, such us medical diagnoses [4], Marketing, sales forecasting, exchange rate predictions [5].

of ANN is due to its ability to handle complex data. ANN appears to be a recent development but it has been developed before the invention of computers. Now due to growth in computational power of computers and advancement in technology ANN is used in various fields like medicine for modeling and diagnosing the cardiovascular diseases, diagnosis of hepatitis, electronic noses-detection, and reconstruction of odors

Guneyisi et. al [6] studied chloride permeability of concrete mixes made of four different cement types and two water-to-binder ratios of 0.65 and 0.45. Samples were tested after 29, 90, and 120 days of curing. ANN models were trained using 70 data sets out of a total of 90 data sets obtained through the experimental program conducted in accordance of ASTM C1202. The remaining 20 data points were used to validate the trained ANN. The ANN model showed an ability to predict the chloride penetration with high accuracy. The input data in this model were the cement type, water/binder ratio and curing days.

Hodhud and Ahmed [7] developed ANN model to predict the chloride diffusion coefficient, which governs the mechanism of chloride diffusion in concrete. A total of 300 concrete mixes with fly ash and blast furnace slag were used to develop the neural network models. Two different ANN models were developed, one model for the concrete mixes with fly ash, and the other is for the concrete that contains blast furnace slag. The input data included water-to-binder ratio, cement content, fly ash content (or slag) content, and curing days. The backpropagation technique was used to develop and train the ANN. The ANN models were able to predict the chloride diffusion coefficient with high degree of accuracy.

Ghafoori et. al [8] studied chloride penetration in SCC mixes using ANN models as well as linear and non-liner regression analyses. Different models were developed by varying the number of input variables. Cement was partially replaced with fly ash and silica fume. The input parameters studied included water-to-binder ratio and the contents of: cement, fly ash, silica fume, course/fine aggregate, and superplasticizer. A total of 12 concrete mixtures with various proportion of water/binder ratio, fly ash and silica fume have been used to develop the models and test the data. A total 72 SCC samples, cured at 28 days, were used to determine the resistance to chloride penetration. A total of 60 samples were used as ANN model training data, and the rest were used for testing. The predicted results from ANN models offered higher accuracy compared to the ones obtained from linear and non-linear regression. Investigators suggested that three input parameters are sufficient to create ANN models with optimum accuracy.

Delvanaz et. al [9] studied the ability of a neural network to predict the chloride diffusion in concrete. 7 concrete mixes with different percentages of silica fume were used to obtain samples to train and test them with the neural network models. Around 24 samples from each concrete mix were cured and experimentally tested 28, 90 and 270 days. The difference between the neural network models are the number of the hidden layers and the number of neurons. The learning algorithm used in the study was gradient descent with adaptive learning rate back-propagation. After applying 7 neural network models, the results showed that water/binder ratio and silica fume content are the best inputs to be used in the model to determine the chloride diffusion in concrete.

Kim et. al [10] developed ANN algorithm and studied chloride diffusion in high performance concrete. 30 different concrete mixes with different proportion were prepared and tested. The validity of the neural network models were compared with the results obtained from accelerated tests, long term submerged test, and field investigation results. The mixes contain silica fume, fly ash and slag with different percentages on each mix. The learning and training algorithm that was used in developing the neural network model is back propagation algorithm.

Ashrafi and Ramezanianpour [11] studied the chloride penetration and chloride diffusion coefficient for concrete mixtures that contains cement type II and silica fume. The mixes investigated contained the following w/b ratios: 0.5, 0.45, 0.4 and 0.35. One ANN model was developed using two input values, namely, w/b ratio and silica fume content and the output was the coulomb charge. A second ANN model uses the same input data while the output data is the chloride diffusion coefficient. The ANN models were trained using the backpropagation algorithm. 70 samples were used to train the model and 18 were used for testing. The results obtained from the neural network models showed that the models are capable of predicting the concrete resistance to chloride penetration.

Oztas et. al [12] developed an artificial neural network ANN model to predict the compressive strength and slump of high strength concrete. The data used to develop and train the ANN model contained 187 concrete mixes collected from the literature. The input layer contained seven parameters including water-to-binder ratio, and the amounts of water, fine aggregates, fly ash, air-entraining agent, superplasticizer, and silica fume. The ANN model showed excellent ability to predict the compressive strength and slump.

Diab and Elyamany [13] investigated the properties of concrete subjected to sulfate attack. The critical concrete properties investigated include expansion, weight loss, and compressive strength. The compressive strength was then determined after 200 days of exposure to sulfate. The cement content, water-to-binder ratio, C3A, sulfate concentration, and curing days were the input parameters for the ANN model. The hidden layer contained 11 neurons. The ANN model showed great ability to predict the concrete properties of interest.

Kwon and Song [14] investigated carbonation on concrete structures. An artificial neural network model was developed to obtain various CO2 diffusion coefficients. The data that was used to build the ANN model was collected from previous experiments. Cement content, water-to-cement ratio, volume of aggregate and relative humidity were input data. The output parameter was the CO2 diffusion coefficient. The results of the ANN model showed that there was a decrease in the diffusion coefficient with high relative humidity and low water-to-cement ratio.

Kewalramani and Gupta [15] investigated the ability of an artificial neural network model to predict the concrete compressive strength measured using ultrasonic pulse velocity. Samples from two concrete mixtures, with different shapes and sizes were produced and tested. The input layer of the ANN model contained the weight and the ultrasonic pulse velocity. The output layer parameter was the compressive strength. The continuous nonlinear sigmoid function was used with the back-propagation algorithm. The results of the ANN model showed good accuracy in predicting the experimental results.

Atici [16] studied the ability of multiple regression analysis and artificial neural network to predict the compressive strength of concrete containing slag and fly ash. A total of 28 different concrete mixes were produced and tested after 3, 7, 28, 90, and 180 days of curing. Six different ANN models were applied with different input parameters. The ANN model was developed and trained using the back-propagation algorithm. The results of the ANN model showed that the predicted values are close to the experimental data.

Topcu and Sarıdemir [17] studied the efficiency of ANN and fuzzy logic models in predicting the compressive strength of mortars containing metakaolin. The results of 179 tested samples obtained from 46 different mix proportions gathered from the literature were used to develop the models. The input layer contained 5 parameters that included the curing age, water-to-binder ratio, metakaolin replacement ratio, superplasticizer and binder-sand ratio. The results showed that both ANN and fuzzy logic models had a strong ability to predict the compressive strength.

Khan [18] studied the compressive strength, tensile strength, gas permeability, and chloride ion penetration of high performance concrete that contained pulverized fuel ash and silica fume. A total 32 mixes were developed with different water-to-binder ratios and the data was used to develop an artificial neural network model to predict the properties of interest. The input layer had eight parameters and the predicted results obtained from the ANN model showed a good correlation with the experimental results.

Chandwani et. al [19] developed the ANN using genetic algorithms to predict the slump of ready mix concrete. The input parameters of the ANN model included cement, fly ash, sand, coarse aggregate, water, and admixture. The hidden layer contained 8 neurons. The genetic algorithm was used to develop the optimal weights for the ANN model in order to minimize the chances of getting local minima. The resulting ANN model showed improved prediction accuracy compared to the traditional back-propagation ANN model.

Yeh [20] developed two models to predict the slump of high performance concrete using second order regression and an artificial neural network model. The ANN model was developed and trained based on 78 mixes. Input layer contained 7 parameters including cement, fly ash, slag, water, superplasticizer, coarse aggregate, and fine aggregates. The hidden layer contained 7 neurons. The ANN model developed offered higher prediction accuracy compared to the second order regression.

This paper is based upon Mohamed et al. [21], who developed ANN models for chloride penetration in SCC mixes using training data obtained from the literature, and validated the model using experimental data where the chloride penetration levels were measured after 7, 14, 28, and 40 days of moist sample curing. However, this paper expands Mohamed et. Al [21] to include: 1) all ANN training data and experimental data obtained through an experimental program conducted by the authors, 2) chloride penetration levels measured after 7, 14, 28, 40, and 70 days of curing.

2. The experimental program

The goal of the experimental program is to study the resistance to chloride penetration of sustainable SCC mixes in which cement is partially replaced with various percentages of fly ash, silica fume, or granulated blast furnace. ANN models are to be developed to predict the chloride penetration levels in SCC mixes. The superplasticizer dosage is kept constant at 7.2 kg/m3 and the water/binder ratio is kept at 0.36. Table 1 shows part of the chloride penetration tests, only 14 data sets measured after curing the samples for 7, 14, 28, 40, and 70 days are shown below. The test samples were prepared and the resistance to chloride penetration was conducted in accordance with ASTM C1202. The data sets shown in Table 1 are used to test the ANN model developed in a subsequent section of this paper.

Table 1: Experimental data sets and chloride penetration measured per ASTM C1202

No	Cement (kg/m^3)	Water	Fly Ash (kg/m^3)	Silica Fume (kg/m^3)	Slag (kg/m^3)	Superplasticizer (kg/m^3)	Basalt Fiber (kg/m^3)	Coarse Aggregate (kg/m^3)	Fine Aggregate (Black Sand) (kg/m3)	Fine Aggregate (Dune Sand) (kg/m^3)	Age (days)	Charge (Coulombs)	Chloride Penetration Remark	Penetration Level
1	480	172.8	0	0	0	7.2	0	800	582.4	313.6	14	4304.7	High	7
2	288	172.8	192	0	0	7.2	2.4	800	582.4	313.6	70	1635.3	Low to Moderate	4
3	288	172.8	192	0	0	7.2	7.2	800	582.4	313.6	7	2683.8	Moderate	5
4	456	172.8	0	24	0	7.2	0	800	582.4	313.6	7	1674.9	Low to Moderate	4
5	96	172.8	96	48	240	7.2	2.4	800	582.4	313.6	70	530.1	Very Low to Low	2
6	96	172.8	48	96	240	7.2	4.8	800	582.4	313.6	70	568.8	Very Low to Low	2
7	96	172.8	72	96	216	7.2	3.6	800	582.4	313.6	70	318.6	Very Low	1
8	360	172.8	96	24	0	7.2	4.8	800	582.4	313.6	70	208.8	Very Low	1
9	96	172.8	120	72	192	7.2	4.8	800	582.4	313.6	70	1032.3	Very Low to Low	3
10	432	172.8	0	48	0	7.2	0	800	582.4	313.6	7	1479.6	Very Low to Low	3
11	432	172.8	48	0	0	7.2	0	800	582.4	313.6	28	2884.95	Moderate	5
12	432	172.8	48	0	0	7.2	0	800	582.4	313.6	14	3292.65	Moderate to High	6
13	288	172.8	192	0	0	7.2	0	800	582.4	313.6	7	3003.3	Moderate to High	6
14	432	172.8	48	0	0	7.2	0	800	582.4	313.6	7	4289.85	High	7

3. The Artificial Neural Network

In order to model the system with a high degree of accuracy, it is necessary to build an ANN model that is capable of modelling the data sets and the parameters that affect the resistance to chloride penetration level. The parameters that are used for creating the schema and training the model are categorized into two types, independent parameters and dependent (target) parameters. Independent parameters include: w/c ratio, cement, blast furnace slag, fly ash, silica fume, water, superplasticizer, coarse aggregate, fine aggregate, age, charge, while target parameter represented by chloride penetration level.

ASTM C1202 recognizes four levels of chloride penetration namely very low, low, moderate, and high. However, given the wide range of charge values measured in this study that fall in the category of low penetration and shown in Table 1, it is likely that reasonable accuracy may not be obtained by using only four levels of chloride penetration. Therefore, for the purposes of the ANN models, chloride penetration levels were categorized into seven bandwidths as shown in Table 2. Each of these levels covers a narrower range of values to simplify the prediction process.

Table 2: Classifications of Chloride Penetration ranges and levels

Chloride Penetration Range	Descriptions	Level
100 – 500	Very Low	1
501 – 1000	Very Low/Low	2
1001 – 1500	Low	3
1501 – 2000	Low / Moderate	4
2001– 3000	Moderate	5
3001 - 4000	Moderate / High	6
>4000	High	7

Training and testing data were collected through an experimental program conducted by the authors. This is done in order to train the model based on local data. The trained model is then validated by comparing the predicted chloride penetration levels with those obtained through experimental measurements.

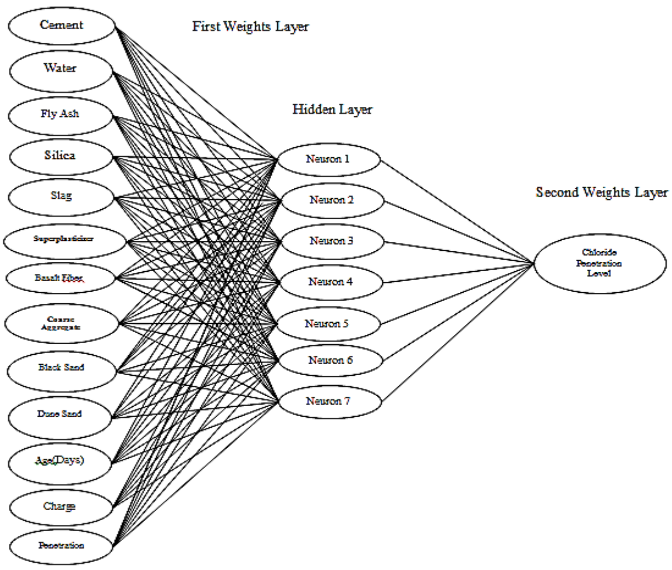
The production of cement is known to contribute significantly to the emission of CO2 into the atmosphere and exacerbate environmental pollution. The partial replacement of cement with mineral admixtures such as fly ash, slag, and silica fume, is presumed to reduce the environmental impact. SCC mixes developed and studied in this research contain various ratios of cement replacement with minerals. Table 3 shows a subset of the 72 SCC mixes that were used to build and train the ANN models of this study. The SCC mixes tested by the authors varied in two ways: 1) the percentage of cement that was replaced by minerals, and 2) type of mineral(s) that was used to replace cement. The cement was partially replaced in each of the SCC mixes by fly ash, slag, silica fume, or combinations of these mixes. In the vast majority of data, the chloride penetration levels in SCC samples fall in the range of very low to medium penetration levels. This is not surprising since these cement replacement minerals are notorious for enhancing the resistance of concrete to chloride penetration.

The fundamental ANN prediction model architecture used in this study is shown in Fig. 4. It includes the input parameters the affect, to various degrees, the resistance to chloride penetration. The ANN model shown in Fig. 4 contains one hidden layer with 7 neurons. A second ANN model that is similar to one in Fig. 4, but contains two-hidden layers, was also studied. For each of the two models, the highest accuracy of prediction was sought by varying the learning rate, momentum, and number of epochs.

Table 3: Partial Part of the training datasets used to train the model

Cement (kg/m^3)	Water	Fly Ash (kg/m^3)	Silica Fume (kg/m^3)	Slag (kg/m^3)	Superplasticizer (kg/m^3)	Basalt Fiber (kg/m^3)	Coarse Aggregate	Fine Aggregate (Black Sand)	Fine Aggregate (Dune Sand)	Age (days)	Charge (Coulombs)	Chloride Penetration Remark	Penetration Level
336	172.8	144	0	0	7.2	0	800	582.4	313.6	28	2163.15	Moderate	5
336	172.8	144	0	0	7.2	0	800	582.4	313.6	40	1759.95	Low to Moderate	4
288	172.8	192	0	0	7.2	0	800	582.4	313.6	14	1667.7	Low to Moderate	4
288	172.8	192	0	0	7.2	0	800	582.4	313.6	70	1285.2	Very Low to Low	2
288	172.8	192	0	0	7.2	2.4	800	582.4	313.6	7	1863.45	Low to Moderate	4
288	172.8	192	0	0	7.2	2.4	800	582.4	313.6	14	1131.3	Very Low to Low	2
288	172.8	192	0	0	7.2	4.8	800	582.4	313.6	7	1475.1	Very Low to Low	2
288	172.8	192	0	0	7.2	4.8	800	582.4	313.6	14	1071	Very Low to Low	2
288	172.8	192	0	0	7.2	4.8	800	582.4	313.6	70	321.3	Very Low	1
288	172.8	192	0	0	7.2	7.2	800	582.4	313.6	14	660.6	Very Low to Low	2
288	172.8	192	0	0	7.2	7.2	800	582.4	313.6	70	599.4	Very Low to Low	2
288	172.8	192	0	0	7.2	9.6	800	582.4	313.6	7	2954.7	Moderate	5
288	172.8	192	0	0	7.2	9.6	800	582.4	313.6	70	580.5	Very Low to Low	2
456	172.8	0	24	0	7.2	0	800	582.4	313.6	70	302.4	Very Low	1
432	172.8	0	48	0	7.2	0	800	582.4	313.6	70	172.8	Very Low	1
408	172.8	0	72	0	7.2	0	800	582.4	313.6	7	279.9	Very Low	1

Fig. 1. Architecture of the ANN model



The architecture of the ANN model shown in Fig. 1, known as the multilayer perception (MLP), the most commonly used ANN. MLPs contain input layer, hidden layer(s), and output layer. In all neural networks, the neurons, shown in Fig. 1, are simple computing elements that contain weights, bias values, and activation functions.

During the ANN training stage, various combinations of learning rates, momentums, and number of epochs were examined. The training process used the backpropagation method where 70% of the training data randomly chosen and tested against every epoch to reduce the error between the actual results and those obtained during every cycle.

Several scenarios needed to be tried in order to generate a trained model based on different number of epochs, learning rate, and momentum. This trained ANN model for each scenario is then used to predict the resistance to chloride penetration based on experimental data that are supplied to the model. The predictions obtained are compared to the experimental results and the accuracy is evaluated as discussed in the following section. Tests conducted within this research cover a wide range of combinations, but the best performing are summarized into 9 different combinations of learning rate, momentums, and number of epochs. The most promising 9 combinations were tested using one and two layers and the results are presented in a subsequent section of this paper.

4. ASSESSMENT OF ANN MODEL PERFORMANCE

Two methods are used to assess the accuracy of prediction of the developed ANN models. The first method is through the Pearson Product-Moment Correlation Coefficient, also known as R-squared, where R is given by Equation (1):

$$R = R_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (1)$$

Where,
: Measured penetration level
: Predicted penetration level
: Mean of the measured chloride penetration level
: Mean of the predicted chloride penetration level

The second method is by calculating the accuracy through the fundamental formula described by Equation (2):

$$Accuracy = 1 - Abs\left(\frac{x_i - y_i}{x_i}\right) * 100 \quad (2)$$

5. Results and discussion

The results of the best 9 scenarios in terms of accuracy are summarized in Table 4 and graphically in Fig. 4. Clearly the higher momentum and learning combinations, demonstrated by scenarios 1 and 2 produced lower prediction accuracy for the two-layer ANN model. Scenario 1 with high momentum and learning rates produced lower accuracy of 0.8329 for the one-layer model only. Decreasing the momentum and learning rate improved accuracy for both one- and two-layer ANN models as demonstrated by scenarios 4 to 9. Comparing scenarios 8 and 9 indicates that increasing the number of epochs improved the accuracy of the two-layer ANN model significantly and improve the accuracy of the one-layer ANN model to a smaller extent.

Table 4: Impact of number of epochs, momentum, and learning

Scenario Number	Set number of epochs, learning rate, and momentum	One Layer Model		Two Layers Model	
		Accuracy	R^2	Accuracy	R^2
1	5000, 0.3, 0.5	75.71	0.8329	83.10	0.8679
2	5000, 0.2, 0.3	94.17	0.9494	84.29	0.8982
3	5000, 0.15, 0.2	93.74	0.9347	80.48	0.8602
4	5000, 0.1, 0.2	96.60	0.9658	91.43	0.9147
5	5000, 0.1, 0.15	96.60	0.9658	91.43	0.9147
6	10000, 0.1,0.15	91.00	0.9147	93.21	0.9347
7	5000, 0.05,0.15	92.36	0.9125	93.38	0.9290
8	5000, 0.05, 0.1	92.36	0.9125	92.19	0.9120
9	10000, 0.05,0.1	91.41	0.9232	94.40	0.9504

Fig. 2 shows that the one-layer ANN model performed generally better than the two-layer model in terms of prediction accuracy, i.e., the one-layer ANN model showed higher sensitivity to the adverse effects of high momentum and learning rate. Once the momentum in decreased from 0.3 in scenario 1 to 0.2 in scenario two, along with a corresponding decrease in learning rate from 0.5 to 0.3, the prediction accuracy increase to 0.9494 in scenario. The accuracy of prediction for the one-layer model remained higher than 0.9 for all scenarios from 2 to 9.

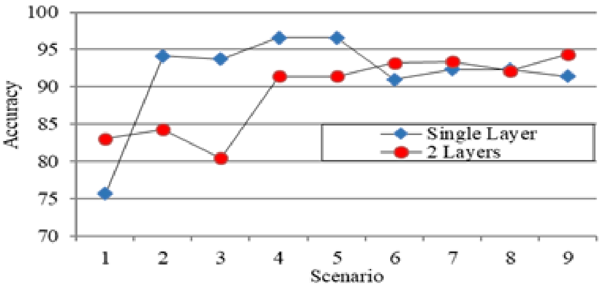


Fig. 2: Accuracy of both single and 2 layers models

It can be seen that a major factor that affecting the accuracy of the model, as expected, is the learning rate. When test is done with the learning rate of 0.3, momentum of 0.5, and number of epochs of 5000 produced an accuracy of 75.71%. This was expected as the learning rate with this much gap indicates that it is missing the actual results. Therefore, the learning rate has to be reduced to the extent that it would produce the most accurate results. Reduction of the learning rate from being 0.3 to 0.2 has increased the accuracy of the model with the momentum having no impact on the accuracy of the model. This can be seen clearly in tests 4 and 5 (accuracy of 96.00%) as well as 7 and 8 (accuracy of 92.36%).

Observing both Table 4 as well as Fig. 4, it can be observed that the accuracy of the model oscillates around the learning rate value of 0. Increase or decrease around this value would decreases the accuracy of the model. Hence, according to the experimental data, the best combination that are needed to achieve higher accuracy in the one-hidden-layer model correspond to a learning rate of 0.1, momentum of 0.1, and 5000 epochs. As for the two layers model, it shows that the highest accuracy was achieved with the learning rate of 0.05, momentum of 0.1, and 10000 epochs.

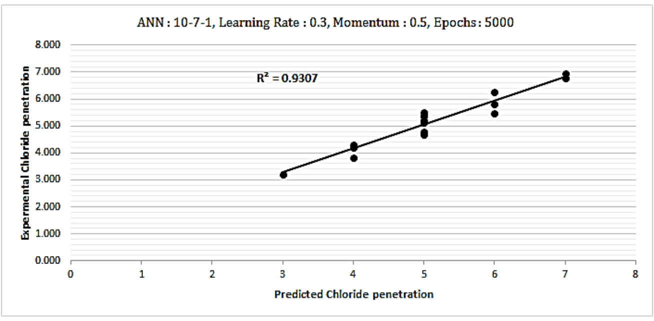


Fig. 3: Prediction accuracy

Fig. 4 shows the accuracy of the predicting the experimental data for the nine combinations of learning rates and momentums for ANN model with one hidden layer. Fig. 4 (T1) represents the initial attempt with a learning rate of 0.3 and momentum of 0.5. This combination resulted in an average accuracy prediction as lows as 75.71%. The remaining combinations are shown in Fig. 5 (T2 to T9). Fig. 5 is similar to Fig. 4, except that the results are for two hidden layers as per table 4.

The overall highest accuracy of prediction of 96.6% was attained for a learning rate of 0.1 and a momentum of 0.15 (scenario 5).

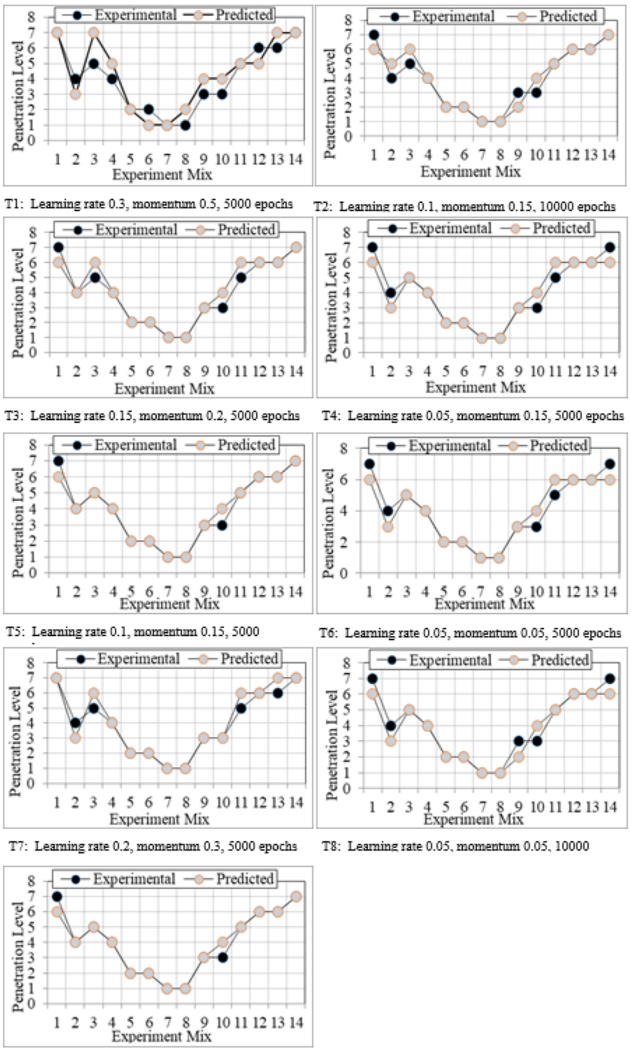


Fig. 4: Predicted versus experimental data for ANN model with single layer

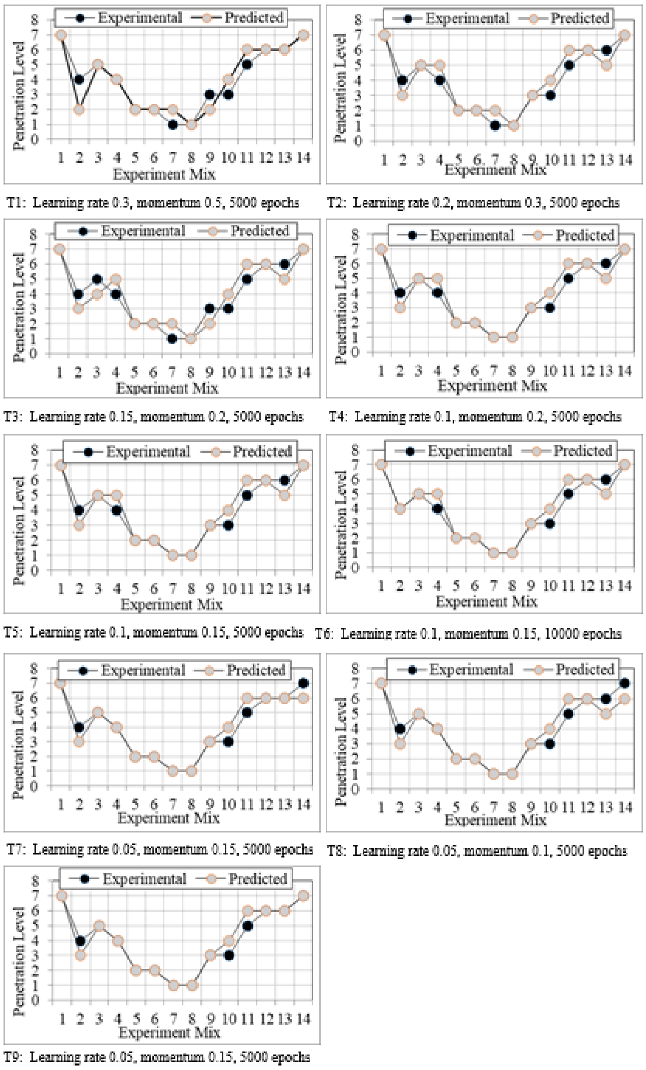


Fig. 5: Predicted versus experimental data for ANN model with two layers

6. Conclusion

The production of cement is known to contribute negatively to environmental pollution. In order to reduce the footprint of the construction industry on the environment, self-consolidating concrete mixes were developed in which cement was partially replaced, at various percentages, with recycled mineral admixtures. The mineral admixtures used to replace cement include fly ash, silica fume, and ground granulated blast furnace slag. The cement in each concrete mix developed in this study was partially replaced with one or more minerals, known for the positive contribution to enhancing resistance to chloride penetration.

ANN models with one and two hidden layers containing 7 neurons were developed and trained using 72 data sets. Emphasise in the study was on the effect on accuracy of prediction of the learning rate, momentum, and number of epochs. Learning rate and momentum were shown to have the highest impact on the accuracy of prediction of ANN models with one- and two hidden layers. The trained ANN models were validated using particularly selected data from the experimental pogrom conducted by the authors. Successfully trained ANN model with learning rate of 0.1, momentum of 0.15, and 5000 epochs on one hidden layer resulted in the highest average prediction accuracy of 96.6%.

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