
# Prediction of chloride penetration in the concrete containing magnetite aggregates by using Adaptive Neural Fuzzy Inference System (ANFIS)

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**Abstract**

This paper aims at predicting chloride penetration in the concrete containing magnetite aggregates by using Adaptive Neural Fuzzy Inference System. The study studied the effect of aggregation types on chloride penetration at 90 days by considering four aggregation types for fine aggregates with fixed soft modulus and making some tests and maintaining them in vitro. In order to establish the terms of the standard chloride, the built prototypes were kept in a solution of water and sodium chloride, and then the experiment of chloride penetration was performed by grinding of the samples at different depths. The results used to predict the chlorine ion penetration by using Neural Fuzzy system. The results of the testing phase of the model have a correlation coefficient above 90% and the error rate is 5%. It indicates that ANFIS can be used in the prediction.

**Key words:** Concrete, Magnetite, permeability, Adaptive Neural Fuzzy Inference System.

## 1. Introduction

Heavy concrete is one of the best and most widely used materials for constructing the shield against nuclear radiation of Neutrons and gamma rays, which on the past, many researchers have conducted studies on its properties. Considering proper distance from population and the residential areas, it is of importance in designing the nuclear facilities with high production capacity to ensure they access to vast resources of water in order to be used in special purposes in various parts of this industry. Therefore, in most cases, most facilities are established near the seas and oceans. Hence, it is important to study the characterizations of such specific type of concrete strength as it is in continuous exposure to the aqueous environment. Since about 75% of the volume of concrete is formed by rock materials, any change in the type of aggregation can make significant importance in the pore structure of concrete and its permeability. In the design of concrete mixing, sand aggregations, is only controlled and monitored by fineness modulus, and placing it in the range of standard grading. In this paper, the changes in the amount of chloride in heavy concrete was studied by keeping these two factors, the effect of the change on the sand aggregation with changing remaining amounts on sieves. For this purpose, four types of aggregations for the sand with fineness modulus, all of which were in the standard aggregation area, and also by considering two different sizes for the coarsest diameter of a grain of sand, the concrete mixing designs were selected, and considered for modeling.

Modeling a system, it is needed to identify a mathematical relationship between input and output data precisely. It is not easy to establish such determined mathematical model and it's required to use some scientific instruments, and special methods. Using neural networks is one of these instruments. In 1998, Yeh proposed a model by using a special type of neural network with incremental neuron that is able to predict the compressive strength of normal concrete. In this model, it was intended seven models of water-cement ratio, water content, cement content, fine aggregate, coarse aggregate amount, coarse size and age of the concrete as the input vector of the neural network. In the year 1999, Basma et al. presented a model based on neural networks, which was able to predict the degree of hydration of cement by using error back propagation algorithms. Malasri et al. predicted the properties of concrete by artificial neural networks in 2006. In 2009, Alshihri presented a model to predict the mechanical properties of concrete by using neural network. In 2011, Jian Ping predicted the 28-day compressive strength with the help of neural network.

In this research, the model of neural fuzzy ANFIS which today is known as one of the best computational systems in the field of engineering is used as a predicting model of chloride penetration in concrete.

## 2. Anfis

In 2000, Jang has introduced the ANFIS architecture (Adaptive Network based Fuzzy Inference System). In ANFIS acchitecture, a FIS is described in a layered, feed-forward network structure where some of the parameters are represented by adjustable nodes and the others as fixed nodes. The raw inputs are fed into the layer 1 nodes that represent the membership functions. The parameters in this layer are called premise parameters and they are adjustable. The second layer represents the T-norm operators that combine the possible input membership grades in order to comput the firing strength of the rule. At least in the basic ANFIS method these parameters are not adjustable. The third layer implements a normalization function to the firing strengths producing normalized firing strength. The fourth layer represents the consequent parameters that are adjustable. The fifth layer represents the aggregation of the outputs performed by weighted summation. It is not adjustable.

Jang introduced two-pass algorithm for adjusting the parameters a modified error backpropagation optimization algorithm. In the forward pass the premise parameters are held fixed and the consequent parameters are adjusted by least squares estimation (LSE). In the backward pass the network error is backpropagated through the network and the premise parameters are adjusted by gradient descend while the consequent parameters are held fixed.

## 3. Used Materials

### Cement

Portland cement type II of cement factory in Ghaen based on the ASTM C150-04 standard and compressive strength of 370 kg/ $cm^{\wedge 2}$ was used in the mixing design of concrete.

**Aggregate**

The rock materials made of magnetite with 60% purity were prepared from the mine in Khaf, located 10 kilometers far from Torbat Jaam. Coarse aggregate of maximum size of 25 and 12.5 mm, and fine aggregates with fineness modulus of 2.83 mm were selected in four different aggregations and according to the ASTM C33 standard aggregation range

## 4. The mixing design

Any results Given the choice between 12.5 and 25 mm maximum sizes of the aggregates, two types of mixings were used, and also regarding this fact that the aggregates have high specific weighs, and applying the minimum amount of water, to some extent, helps to a decrease in concrete shrinkage and separation of aggregates, it was used a unique water-cement ratio (W/C= 0.4) in the mentioned mixing design. Finally, 8 mixings, as described in Table 1 were considered for modeling.

| The mixing design for maximum size of grain of 25 mm | | | | | |
|---|---|---|---|---|---|
| The design code | Sand aggregation | Cement (kg) | Water (kg) | gravel (kg) | Sand (kg) |
| SP 25-1 | Type 1 | 505 | 202 | 1616.141 | 1072.109 |
| SP 25-2 | Type 2 | 505 | 202 | 1616.141 | 1072.109 |
| SP 25-3 | Type 3 | 505 | 202 | 1616.141 | 1072.109 |
| SP 25-4 | Type 4 | 505 | 202 | 1616.141 | 1072.109 |
| The mixing design for maximum size of grain of 12.5 mm | | | | | |
| The design code | Sand aggregation | Cement (kg) | Water (kg) | gravel (kg) | Sand (kg) |
| SP 12.5-1 | Type 1 | 575 | 230 | 1367.5 | 995.72 |
| SP 12.5-2 | Type 2 | 575 | 230 | 1367.5 | 995.72 |
| SP 12.5-3 | Type 3 | 575 | 230 | 1367.5 | 995.72 |
| SP 12.6-4 | Type 4 | 575 | 230 | 1367.5 | 995.72 |

Table 1. The used mixing designs in making samples

## 5. Maintenance Environment

Maintaining the tests, the solution of water and sodium chloride with concentration of 165 gr/lit and the temperature of 23 ° C was used based on the Nord Test Build 443 standard, and these conditions were maintained throughout the test period.

## 6. Chloride ion penetration test

To test the chloride ion penetration, some cubic tests with dimensions of 15 x 15 x 15 cm were used. After 90 days of exposure of cubic samples in a pool containing sodium chloride, sampling operations were performed to determine the chloride ion penetration. For this purpose, at least 10 grams of concrete powder was prepared by using the method of drilling on the sample surface at the depths of 1-0, 2-1, 3-2, and 4-3 cm (figure 1). After providing concrete powder samples at different depths, the experiment of chloride ion penetration was performed by using potentiometric electrochemical (ASTM C1152 standard) (figure 2); the results are presented in Table 2.

**Fig1**. Grinding the concrete samples

**Fig2**. Measurement of chloride ion percentage in the sample by using the Potentiometric

| Depth (cm) | Design code | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SP 25-1 | SP 25-2 | SP 25-3 | SP 25-4 | SP 12.5-1 | SP 12.5-2 | SP 12.5-3 | SP 12.5-4 |
| 0-1 | 0.75 | 0.8 | 0.65 | 0.55 | 0.55 | 0.75 | 0.55 | 0.45 |
| 1-2 | 0.45 | 0.65 | 0.45 | 0.35 | 0.40 | 0.55 | 0.35 | 0.30 |
| 2-3 | 0.35 | 0.45 | 0.3 | 0.25 | 0.30 | 0.35 | 0.25 | 0.20 |
| 3-4 | 0.25 | 0.35 | 0.2 | 0.15 | 0.20 | 0.30 | 0.15 | 0.10 |

Table 2. Chlorine percentage based on the weight of concrete in 90 days

## 7. Determining the data of Neural Fuzzy model

In this paper, two Neural Fuzzy models were determined to predict the changes of chloride penetration in heavy concrete. The first model was considered based on the maximum size of coarse aggregate of 25 mm, and the second model was for the maximum size of coarse aggregate of 12.5 mm.

In determining the type of input data, according to the four types of different used sand aggregations, there were a lot of input variables, and since existing these many variables require large amounts of input data to train a predictive model, a way should be used by which it was possible to determine some variables for the model, which not only include all entries, but possess appropriate values to predict chloride penetration and reduce the errors in output numbers of the model. To achieve this goal, the linear regression was used. Thus, a linear equation was determined by performing regression based on the values passing each sieve for each type of sand, and the equation coefficients were used as input variables of ANFIS. In determining this equation, the passing percentage of all sieves was ignored, except the 100 sieve due to its constant value in all aggregates, and also because of creating errors in the regression equation. Finally, only two input variables from the regression equation coefficients were used as the representatives of aggregations of each types of sand. Regression diagrams and their equations with obtained coefficient values are shown in Figures 3 to 6. In these figures, data related to figures 1 to 5 is the passing percentage of the 4, 8, 16, 30, and 50 sieves respectively.

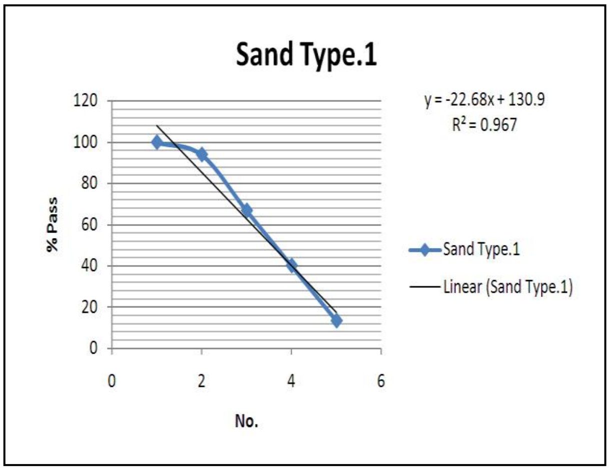


**Fig3**. Linear regression of sand aggregation type 1

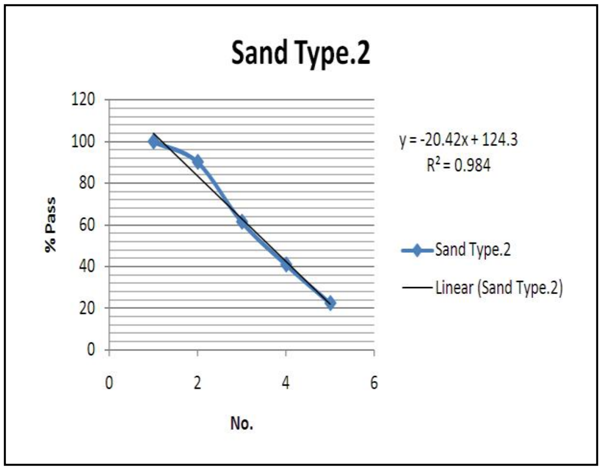


**Fig4.** Linear regression of sand aggregation type 2

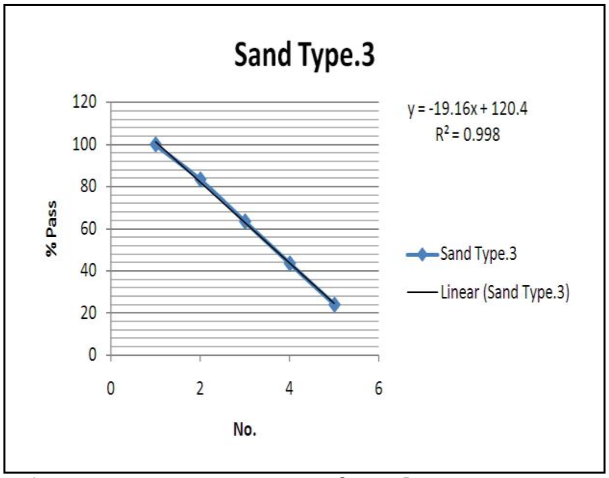


**Fig5.** Linear regression of sand aggregate type 3

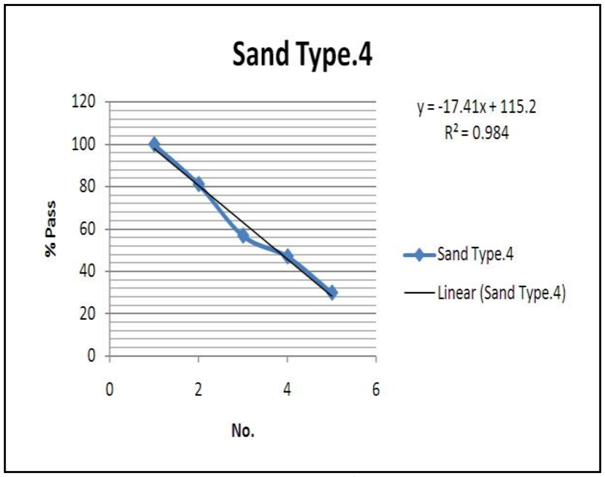


**Fig6**. Linear regression of sand aggregate type 4

Regarding the obtained equations for each type of sand, the amount of input data is measured based on the constant value of the equation, 3 selected variables included in X coefficient of the regression equation, and finally the grinding depth, as shown in Tables 3 and 4. Output variable ANFIS is the percentage of chloride penetration.

| Agregate | Input1: H(cm) | Input2: X-Factor | Input3: Const. | Output: %Cl |
|---|---|---|---|---|
| Type 1 | 1 | -22.68 | 130.90 | 0.55 |
| Type 1 | 2 | -22.68 | 130.90 | 0.4 |
| Type 1 | 3 | -22.68 | 130.90 | 0.3 |
| Type 1 | 4 | -22.68 | 130.90 | 0.2 |
| Type 2 | 1 | -20.42 | 124.30 | 0.75 |
| Type 2 | 2 | -20.42 | 124.30 | 0.55 |
| Type 2 | 3 | -20.42 | 124.30 | 0.35 |
| Type 2 | 4 | -20.42 | 124.30 | 0.3 |
| Type 3 | 1 | -19.16 | 120.40 | 0.95 |
| Type 3 | 2 | -19.16 | 120.40 | 0.7 |
| Type 3 | 3 | -19.16 | 120.40 | 0.45 |
| Type 3 | 4 | -19.16 | 120.40 | 0.4 |
| Type 4 | 1 | -17.41 | 115.20 | 0.45 |
| Type 4 | 2 | -17.41 | 115.20 | 0.3 |
| Type 4 | 3 | -17.41 | 115.20 | 0.2 |
| Type 4 | 4 | -17.41 | 115.20 | 0.1 |

Table 3. Data values of input and output variables of the maximum size of the coarse aggregate of 25 mm for the first model

| Agregate | Input1: H(cm) | Input2: X-Factor | Input3: Const. | Output: %Cl |
|---|---|---|---|---|
| Type 1 | 1 | -22.68 | 130.90 | 0.75 |
| Type 1 | 2 | -22.68 | 130.90 | 0.45 |
| Type 1 | 3 | -22.68 | 130.90 | 0.35 |
| Type 1 | 4 | -22.68 | 130.90 | 0.25 |
| Type 2 | 1 | -20.42 | 124.30 | 0.8 |
| Type 2 | 2 | -20.42 | 124.30 | 0.65 |
| Type 2 | 3 | -20.42 | 124.30 | 0.45 |
| Type 2 | 4 | -20.42 | 124.30 | 0.35 |
| Type 3 | 1 | -19.16 | 120.40 | 1.1 |
| Type 3 | 2 | -19.16 | 120.40 | 0.75 |
| Type 3 | 3 | -19.16 | 120.40 | 0.55 |
| Type 3 | 4 | -19.16 | 120.40 | 0.45 |
| Type 4 | 1 | -17.41 | 115.20 | 0.55 |
| Type 4 | 2 | -17.41 | 115.20 | 0.35 |
| Type 4 | 3 | -17.41 | 115.20 | 0.25 |
| Type 4 | 4 | -17.41 | 115.20 | 0.15 |

Table 4. Data values of input and output variables of the maximum size of the coarse aggregate of 12.5 mm for the second model

## 8. Modeling

Of all 16 pairs of existing input - output data, 12 cases were considered to teach the model and four remaining pairs to test the model. These data were then normalized and random in the range of 0.1 to 0.9 were entered into the model.

## 9. Selecting the model

Selecting the hybrid learning method and linear output function, the best modeling results with good correlation and low error were obtained by the model of network isolating. Number of membership functions of the selected models 3 and the selected equation is dsigf.

## 10. Conclusions

The results of the ANFIS model with actual values of compressive strength are shown in Tables 7 and 8. As the tables show, the values obtained from Neural Fuzzy model consist of few errors. The correlation of the data in the first model was 97% and for the second one was 92%. Figures 7 and 8 show the predicted values by the model against the actual values.

| | Output | Output-Net |
|---|---|---|
| Data1 | 0.4 | 0.42 |
| Data2 | 0.4 | 0.35 |
| Data3 | 0.35 | 0.36 |
| Data4 | 0.75 | 0.75 |

Table 7.
The results of the Neural Fuzzy No. 1 (the maximum size of the coarse aggregate of 25 mm)

| | Output | Output-Net |
|---|---|---|
| Data1 | 0.3 | 0.32 |
| Data2 | 0.55 | 0.46 |
| Data3 | 0.3 | 0.34 |
| Data4 | 0.45 | 0.45 |

Table 8.
The results of the Neural Fuzzy No. 2 (the maximum size of the coarse aggregate of 12.5 mm)

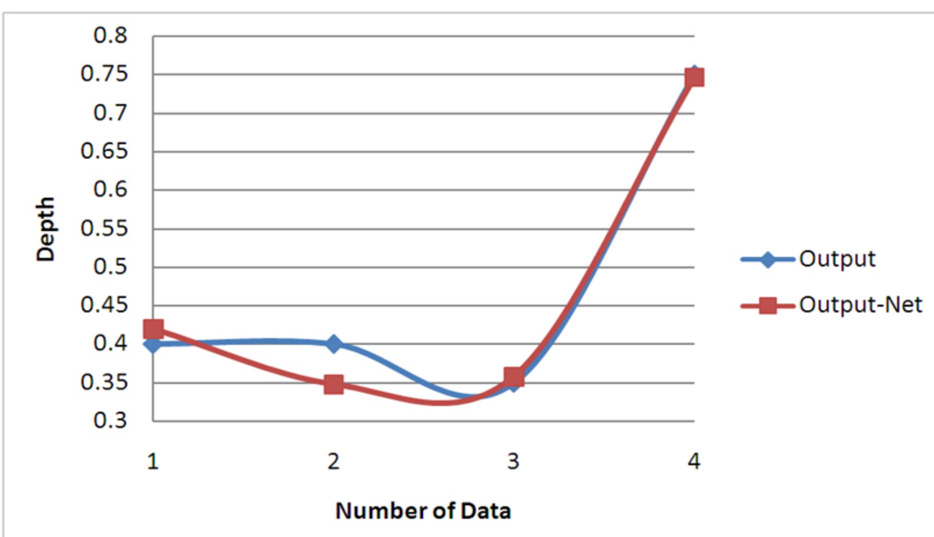

**Fig7**. The representation of the results of the Neural Fuzzy No. 1 (the maximum size of the coarse aggregate of 25 mm)

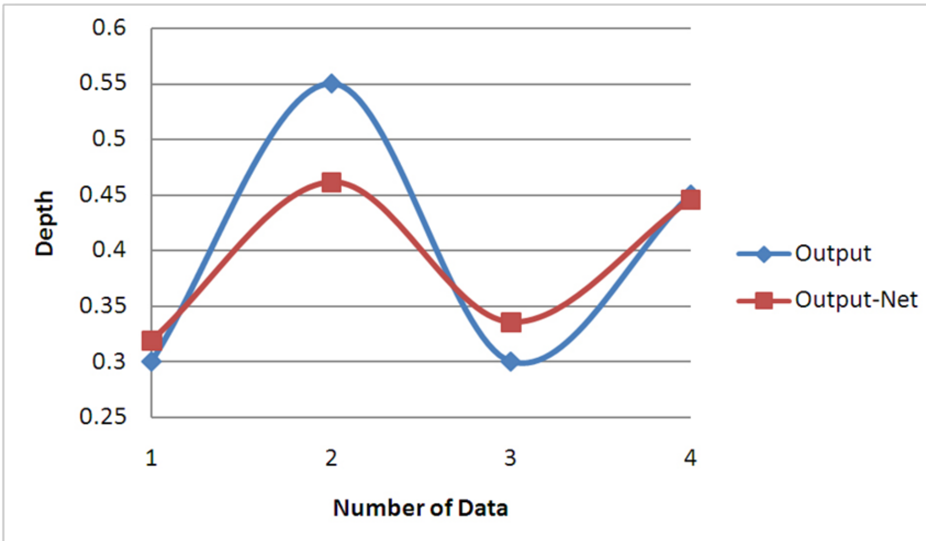


**Fig8**. The representation of the results of the Neural Fuzzy No. 1 (the maximum size of the coarse aggregate of 12.5 mm)

## 11. References

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