# A Suitable Neural Network Design Based on Statistical Analysis for Concrete Prediction of both Compressive Strength and Abrasion Resistance

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*ABSTRACT*

Concrete is known as a durable construction material, which is widely used in many structures. In Iran due to internal production of cement and steel bars and existence of suitable aggregates, concrete is used in most of structures such as industrial floors, external floors, concrete structures, etc. In many cases, due to low abrasion resistance of concrete, durability and service life of industrial floors is low. Abrasion resistance of concrete is related to several parameters such as quality of materials, concrete mix design, water to cement ratio, curing condition and compressive strength. In this paper, the effect of some of the above parameters on [iv]compressive strength and abrasion resistance of concrete and interaction of them are investigated based on statistical analysis. In addition, based on a neuro, prediction of compressive strength and abrasion resistance has been done based on statistical analysis results. Finally, some suggestions about the optimum numbers of hidden neurons have been presented. Finally, best selection of input parameters for optimizing learning time is discussed.

*KEYWORDS*

Abrasion; Statistical procedures; Neural networks; Polymer; Silica fume; Concrete mix design

## 1. INTRODUCTION

Low abrasion resistance of concrete is the cause of deterioration in many countries, which is mainly due to 1) unsuitable concrete mix designs, 2) high water-binder ratio, 3) poor construction, 4) low-quality of aggregates, 5) poor curing condition, 6) admixture and additives, etc [1]. Neural networks are widely used in civil engineering, such as optimization of structures, optimal control of structures, analysis and design of structures, design of expert systems and concrete mix designs [2-6]. Neural networks can be used for predicting the service life of structures and structural elements. Nowadays, almost all of the concrete mixed designs have been developed based on durability problems in severe environmental conditions. For this reason, using neural networks based on the existing data, past experiences and constructed concretes can help for a better prediction of service life of concretes especially abrasion resistance. In this paper, data analysis is done based on some statistical procedures. Then, these procedures are used to investigate the effects of parameters such as Water-binder ratio, Silica fume percentage, polymer percentage, type of aggregate, period of curing and type of surface finishing and their interactions on abrasion resistance and compressive strength of concrete. It should be noted that the type of surface finishing affects only abrasion resistance of concrete. The outcomes of the statistical analysis are finally used by some properly developed MLP based neural networks to predicate compressive strength and abrasion resistance. The rest of this paper is organized as follow:

Section 2 presents the data sets that are used in this research for statistical analysis and networks training. In section 3 the factorial statistical method carried out on data sets given in section 2 and the effect of parameters and their interactions on compressive strength and abrasion resistance are calculated. Section 4 shows how to

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select a suitable set of input entries in order to reduce the amount of learning time based on statistical analysis. Finally, section 5 concludes the paper.

## 2. ABRASION EXPERIMENTAL DATA

In this paper, the results of experimental test carried out by Haggollahi[1] have been used. In that research, the effect of type of aggregate (granite or normal aggregate), water-binder ratio, silica fume replacement level, polymer percentage, period of curing and type of surface finishing on compressive strength and abrasion resistance were investigated. Water-binder ratio is varied 0.3-0.45 and silica fume and polymer percentage is considered 0%, 5% and 10% by mass of cement. Road Note4 is used for concrete mix design of specimens. The Portland cement Type (I) is used in specimens. Fifteen hundred millimeter concrete cubes for compressive strength and 30.5×30.5×9.5 cm flat concrete specimens for abrasion resistance were tested after 3-days, 7-days, 28-days and 90-days. Specimens were cast and allowed to remain in the molds for 24 h before demolding. Type of polymer that is used in this research is S.B.R. Specimens were tested based on ASTM C779-89 and results were represented as the depth of abrasion of specimens [1]. The total number of data sets was 432 and 80% of the data randomly selected and used for training of networks and 20% remaining data used for testing networks. It should be noted that the type of surface finishing only affects abrasion resistance of concrete.

## 3. THE EFFECTS OF PARAMETERS AND THEIR INTERACTION

The factorial statistical method has been used to investigate the effect of parameters and their interactions on compressive strength and abrasion resistance of concrete. It should be noted that due to limitation of number of tests, only one specimen was used in each of tests given in the previous work [1]. Parameter mean squares and their interactions are calculated using Table 1[8]. In this table, equations for calculating the mean squares, degree of freedom of two factors (e.g., parameters A and B), their interaction (A×B), the errors term and the total sum of mean squares are shown. A and B represent any two factors (parameters), i =1,2,..., α and j=1,2,..., b represent levels of factor A and B, respectively, k=1,2,..., n is observation per cell that in this research n is equal to 1, $\varepsilon_{k(ij)}$ is the errors with in treatments, $Y_{(ijk)}$ represents the $ith$ and $jth$ observation on the $kth$ treatment (k=1,2,...,n), $T_{i..}$ and $T_{.j.}$ represent the total number of the observations taken under treatment i and j respectively, and, $T_{...}$ represents the grand total number of all observations formulated as :

$$T_{...} = \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n} Y_{ijk} = \sum_{j=1}^{b} T_{.j.} = \sum_{i=1}^{a} T_{i..}$$

If number of parameters exceeds 2, Table 1 can be developed for any number of parameters [8].

TABLE1. GENERAL ANOVA FOR TWO-FACTOR FACTORIAL WITH $N$ REPLICATIONS PER CELL [8]

| Source | df | SS | MS |
|---|---|---|---|
| Factor $A_i$ | α-1 | $\sum_i^{\alpha} \frac{T_{i..}^2}{nb} - \frac{T_{...}^2}{nab}$ | Each SS divided by its df |
| Factor $B_j$ | b-1 | $\sum_j^{b} \frac{T_{.j.}^2}{n\alpha} - \frac{T_{...}^2}{nab}$ | |
| Interaction $A \times B$ | (α-1)*( b-1) | $\sum_i^{\alpha}\sum_j^{b} \frac{T_{ij.}^2}{n} - \sum_i^{\alpha} \frac{T_{i..}^2}{nb} - \sum_j^{b} \frac{T_{.j.}^2}{n\alpha} + \frac{T_{...}^2}{nab}$ | |
| $\varepsilon_{k(ij)}$ Errors | $\alpha b(n-1)$ | $\sum_i^{\alpha}\sum_j^{b}\sum_k^{n} Y_{ijk}^2 - \sum_i^{\alpha}\sum_j^{b} \frac{T_{ij.}^2}{n}$ | |
| Totals | $\alpha bn - 1$ | $\sum_i^{\alpha}\sum_j^{b}\sum_k^{n} Y_{ijk}^2 - \frac{T_{...}^2}{n\alpha b}$ | |

For example, in this paper, levels of water-binder ratios are 0.3, 0.35 and 0.4. Therefore, if this parameter is denoted by A, then α =3, and degree of freedom of this parameter is evaluated from (α-1) and appears to be equal to 2.

By developing Table 1 for other parameters, degree of freedom, SS, MS of any parameter, their interactions, the errors term and totals are calculated and shown in Tables 2 and 3 for compressive strength and abrasion resistance.

Table2. The results of statistical analysis for compressive strength

| Source | df | SS | MS | F Test | Prob. |
|---|---|---|---|---|---|
| Period of curing (T) | 3 | 21075.4 | 7025.14 | 457.8 (****) | 0.000 |
| Type of aggregate (A) | 1 | 3563.7 | 3563.7 | 232.2 (*) | 0.0557 |
| A*T | 3 | 440.84 | 146.95 | ------ | ------ |
| Silica fume (S) | 2 | 977.25 | 488.62 | 31.8 (**) | 0.0346 |
| S*T | 6 | 74.3 | 12.38 | ------ | ------ |
| S*A | 2 | 12.435 | 6.22 | ------ | ------ |
| Water-binder ratio( W) | 2 | 4836.6 | 2418.3 | 157.6 (***) | 0.0071 |
| Polymer percentage( P) | 2 | 14.26 | 7.13 | 0.46 | Not Significant |
| P*S | 4 | 53.49 | 13.37 | ------ | ------ |
| Errors | 205 | 3145.82 | 15.346 | ------ | ------ |
| Total | 215 | 33613.03 | ----- | ------ | ------ |

In Tables 2 and 3, degree of freedom of error has been calculated as total degree of freedom minus degree of freedom of parameters (without subtract of interactions degrees of freedom). The reasons why we are calculating error degree of freedom in this way are:

1. The errors degree of freedom is equal to zero in normal case because of n=1.
2. Interaction of parameters is negligible after calculating them by statistical methods [8].

Table3. The results of statistical analysis for abrasion resistance

| Source | df | SS | MS | F Test | Prob. |
|---|---|---|---|---|---|
| Period of curing (T) | 3 | 7.015 | 2.338 | 44.62 (****) | 0.000 |
| Type of aggregate (A) | 1 | 5.28 | 5.28 | 100.76 (*) | 0.0902 |
| A*T | 3 | 0.4732 | 0.158 | ------ | ------ |
| Silica fume (S) | 2 | 1.44 | 0.72 | 13.74 (**) | 0.0788 |
| S*T | 6 | 0.1393 | 0.0232 | ------ | ------ |
| S*A | 2 | 0.1585 | 0.0793 | ------ | ------ |
| Water-binder ratio (W) | 2 | 1.388 | 0.694 | 13.24 (**) | 0.08125 |
| W*T | 6 | 0.0877 | 0.0146 | ------ | ------ |
| W*A | 2 | 0.1334 | 0.0667 | ------ | ------ |
| Polymer percentage (P) | 2 | 0.624 | 0.312 | 5.954 | Not Significant |
| Type of surface finishing) C) | 1 | 1.1 | 1.1 | 20.99 | Not Significant |
| Errors | 420 | 2.2014 | 0.0524 | ------ | ------ |
| Total | 431 | 19.0484 | ----- | ------ | ------ |

Parameter's mean squares are calculated by dividing sum of parameter squares to its degree of freedom. In Tables 2 and 3, the F test column is calculated by dividing mean squares of any parameter to the mean squares of error. Magnitudes of this column are then compared with F distribution tables in order to obtain the amount of the effect of each parameter can have.

Due to high value for interaction between type of aggregate and period of curing, mean of data for compressive strength and abrasion resistance are shown in Figs. 1 and 2. In these Figures, "1" and "2" on horizontal axes represent normal and granite aggregates, respectively. Because the lines in Figs. 1 and 2 are parallel, we may say that interaction between two parameters (period of curing and type of aggregate) is negligible.

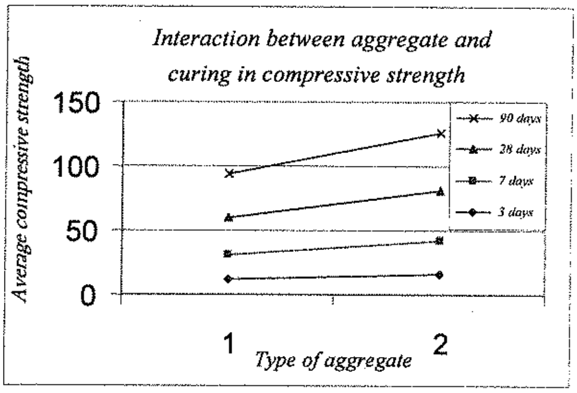


Fig 1. Interaction of type of aggregate and period of curing on compressive strength

*Interaction between aggregate and curing in Abrasion*

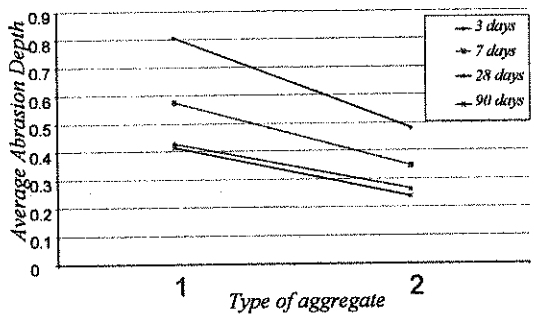


Fig 2. Interaction of type of aggregate and period of curing on abrasion resistance.

Based on Tables 2-3 and Figs. 1-2 the following results are listed:

*a) Effect of parameters on compressive strength:*

1- Effect of water-binder ratio is higher than the others, except for the period of curing. Therefore, the effect of period of curing on compressive strength is very important.

2- Silica fume improves compressive strength, and its effect is higher than that of the type of aggregate. The reason of this problem is the difference between degree of freedom of type of aggregate and silica fume. Therefore, comparing the effect of these parameters is not correct.

3- The effect of polymer on improving compressive strength is negligible. Therefore, it can be suggested not to use polymers for increasing compressive strength.

4- Interaction between parameters is negligible. Therefore, the effect of any parameter on compressive strength can be evaluated independently.

*b) Effect of parameters on abrasion resistance:*

1- The effect of water-binder ratio and silica fume is nearly equal, and their effects are larger than the others except for a period of curing. Therefore, the effect of period of curing on abrasion resistance is also very important.

2- The effect of polymer for improving abrasion resistance is not significant and is nearly equal to 43% of that of the silica fume.

3- The effect of type of surface finishing on increasing abrasion resistance is not significant and is nearly to 25% of that of the type of aggregates. However, surface finishing should be implemented after concrete placing.

4- Interaction between parameters is negligible. Therefore, the effect of any parameter on abrasion resistance can be evaluated independently.

## 4. SUITABLE SELECTION OF NEURAL NETWORK INPUT PARAMETERS BASED ON STATISTICAL ANALYSIS

In this section, first ordinary MLP based neural networks have been used for prediction of compressive strength and abrasion resistance. Second, selected input parameters based on data analysis given in section 3 has been used for training of neural networks followed by some comparison studies.

### *A. The Usual MLP*

To predict compressive strength and abrasion resistance, two neural networks are used independently. The results of experiments carried out in reference [1] are used for training networks. The design inputs are: Type of aggregates, Water-binder ratio, Silica fume content, Polymer percentage, Period of curing and type of surface finishing. It should be noted that the type of surface finishing only affects the abrasion resistance. Therefore, this parameter is only used in predicting abrasion resistance as an input data. Due to suitable correlation between abrasion resistance and compressive strength, compressive strength is used as an input parameter in the second neural network to predict abrasion resistance. It should be noted that for training the networks the real value of input parameters are considered except the type of aggregates and the type of surface finishing. For the type of aggregates, numbers 1 and 0 are considered for normal and granite aggregate, respectively. Also, for machine and hand-surface finishing, numbers 1 and 0 are used, respectively. Number of output layer neurons for two networks is 1. The output of two networks indicates compressive strength and abrasion resistance, respectively. Multilayer Perceptron is used for two networks and their schematic model of the neural networks is shown in Fig 3.

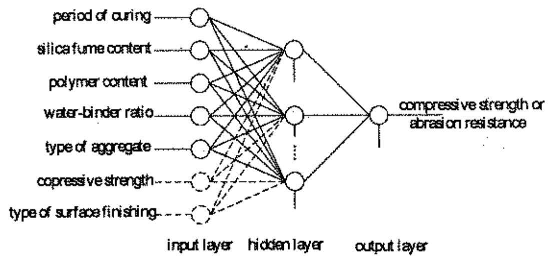


Fig 3. Schematic model of the neural network with one hidden layer

First, by using back propagation algorithm, networks are constructed with one hidden layer, and then trained. Number of neurons in the hidden layer is considered to vary. Fig. 4 shows how the numbers of hidden neurons affect the performance of the neural networks. This figure plots the mean square errors after 10 cycle of training.

In Fig 4, it is evident that the first local minimum will occur when the number of neurons in hidden layer is equal to the number of input parameters. Therefore, at first, for the purpose of better training, it is suggested to assume the number of neurons in the hidden layer is equal to the number of input parameters. Then, if the network's response is not suitable, the number of neurons should be changed and the network should be trained again.

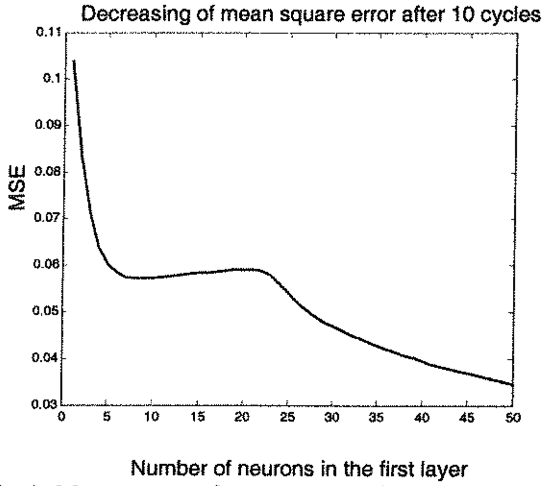


Fig 4. Mean square of errors curve related to the number of hidden layer neurons in neural network for the abrasion prediction problem

It should be noted that the learning rate mainly affects the convergence speed of the network. Due to the large number of input parameters and using only one hidden layer in the networks for training, the value of the learning rate should be considered as a very low number. If learning rate becomes large, the network will diverge. Fig 5 presents the plot of mean square errors after 20 cycles in the abrasion resistance prediction network with 7 neurons in the hidden layer. It is evident that the learning rate of 0.0005 yields a better performance.

Mean square error after 20 cycles for prediction of abrasion resistance

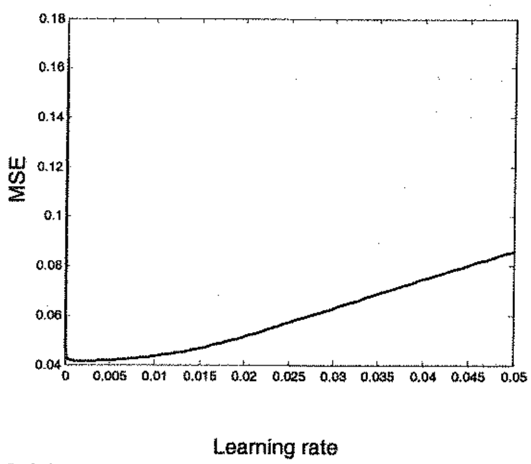


Fig 5. Mean square errors curve related to the learning rate in neural network for predicting the abrasion resistance

The mean square errors for two neural networks with the proper learning rate and number of hidden neurons are shown in Figs 6 and 7. Mean square errors after 100 cycles with 5 neurons in the hidden layer are 53.0999. These values are not ideal for network. After 500 cycles this value decreases to 50.4529. Therefore, better learning needs more time. Widely range of compressive strength, varying from 5.0 to 60.0 MPa, and using linear activation function in output layer, are reasons for the low learning rate.

Decreasing in mean square error for compressive strength prediction

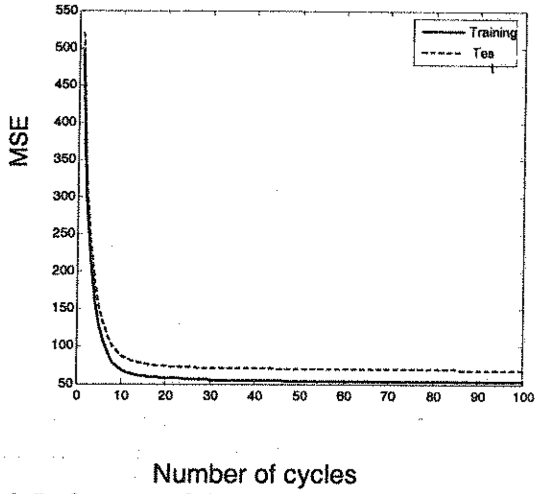


Fig 6. Performance of the proposed network for compressive strength prediction

However, in the second network with 7 hidden neurons and the same learning rate used to predict abrasion resistance, mean square errors after 100 cycles reaches to 0.0436 (see Fig7). Limitation in the range of abrasion depth, varying from 0.2 to 1.4mm, is the major reason for ideal learning of this network. Increasing the number of hidden layers does not affect the learning performance noticeably as shown in Fig.8.

Decreasing in mean square error for abrasion resistance prediction

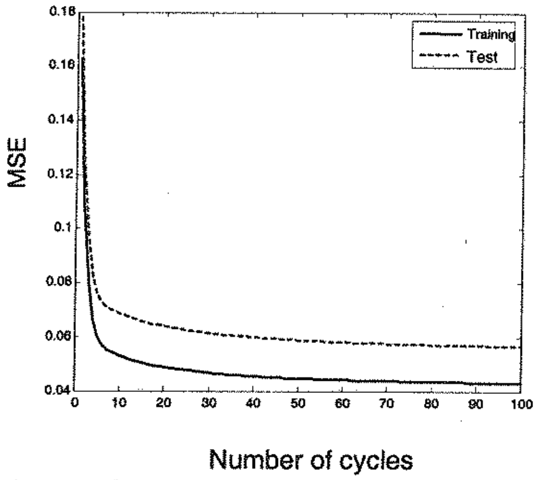


Fig 7. Performance of the proposed network for abrasion resistance prediction

Mean square error after 20 cycles

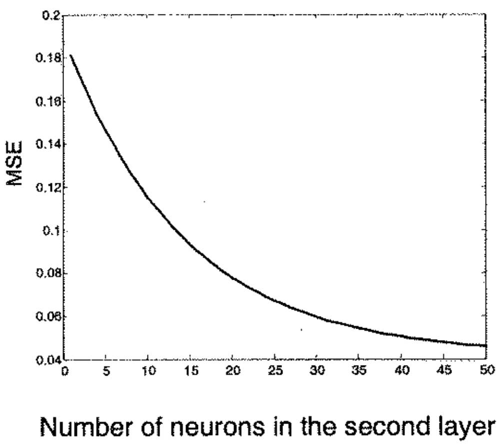

Fig 8. Mean square errors curve related to the number of neurons in the second hidden layer for predicting the abrasion

*B- Suitable selection of input parameters based on data analysis*

Effects of any parameter on compressive strength and abrasion resistance of concrete were calculated in section 3. Based on Tables 2 and 3, the effect of polymer percentage on both compressive strength and abrasion resistance is not significant. Furthermore, the effect of type of surface finishing on abrasion resistance is not significant. Therefore, these parameters could be omitted from input parameters.

Also, if the interactions of the parameters (e.g., A, B,...., M) were significant, these interactions could be added to the input parameters. Each interaction parameter ($I$) should be calculated by the following equation:

$$I = A \times B \times \ldots \times M \qquad A, B, \ldots, M \neq 0$$

In this research, because all of interactions are not significant, these interactions are not considered as input parameters. A schematic model of neural networks used in the paper is shown below.

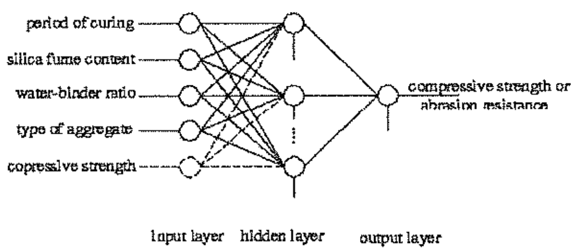

Fig 9. Schematic model of the neural network with omitted input parameters

This network was trained and compared with the one given in the previous section. Fig 10 shows the performance of two neural networks in the prediction of abrasion resistance. It is evident that the performance of the network with less number of inputs has not been degraded while the network becomes more simple and requires less time for training.

Decreasing in mean square error for abrasion resistance prediction

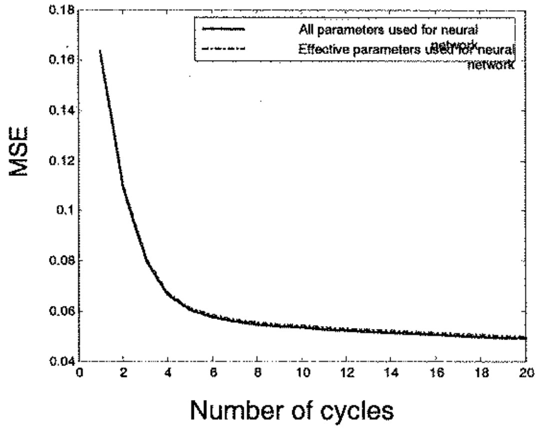

Fig 10. Performance of two neural networks with 7 neurons in the hidden layer

## 5. CONCLUSIONS

In this paper, statistical procedures for better evaluation of test results have first been designed. Then, proper MLP like neural networks based on statistical procedures are developed to predict compressive strength and abrasion resistance of concrete. The following conclusions are drawn:

1- Period of curing is the most effective parameter on the compressive strength and abrasion resistance of concrete.
2- Low water-binder ratio in concrete mixtures enhances compressive strength and abrasion resistance of concrete.
3- The use of silica fume and appropriate aggregates (e.g., granite aggregate) increase compressive strength of concretes. However, compressive strength of concretes decreases when polymer is added to the mixtures.
4- The use of appropriate aggregates and also silica fume enhance the abrasion resistance of concrete.
5- Effects of polymer and type of surface finishing an abrasion resistance are not significant.
6- The effect of interaction of parameters on compressive strength and abrasion resistance of concrete is negligible. Therefore, the effect of any parameters can be evaluated separately.
7- The neural network is suitable method for prediction of abrasion resistance.
8- Number of hidden layer neurons is considered equal to the number of input parameters.
9- For selection of suitable input parameters of neural networks statistical analysis should be carried out.

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