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Original Research Paper- Engineering

Investigating the Effect of Adding Nanosilica on Compressive Strength and Electrical Resistance of Concrete at Different Water-Cement Ratios and Predicting it Using Artificial Neural Networks

Corresponding Author:
Arash Alipour
Department of civil Engineering, Faculty of Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran.

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ABSTRACT:
Nanotechnology has brought about remarkable advancements in human knowledge and has attracted substantial attention from researchers across various scientific fields. Nanoparticles possess unique physical and chemical properties that have paved the way for the production of novel materials with exclusive capabilities. In civil engineering, one such application is the use of nanosilica, a nanotechnology product, as a highly reactive artificial pozzolan to partially substitute cement in concrete mix designs, potentially improving the properties of concrete.
In recent years, artificial neural networks, a branch of artificial intelligence, have been employed to address many civil engineering problems. The fundamental concept behind this method is inspired by the way the human brain's neural system processes data and information for learning and knowledge generation. A neural network comprises a desired number of processing units (neurons, cells, nodes) arranged in layers, which relate the input set to the output set. Essentially, neural network models can be regarded as complex linear or non-linear regressions, trained on input data and target outputs, capable of predicting conditions based on new inputs. The experimental results in this study demonstrate that the use of nanosilica additive and the reduction of the water-to-cement ratio increase the compressive strength and electrical resistance of concrete. Furthermore, by considering different amounts of nanosilica additive for various water-to-cement ratios at 7 and 28 days as the network input, the designed artificial neural network model performs satisfactorily in predicting the compressive strength and electrical resistance indices of concrete.

Keywords: Compressive Strength, Electrical Resistance, Nanosilica, Artificial Neural Network.

1. INTRODUCTION

The durability or sustainability of concrete is associated with its service life or age under specified environmental conditions. It is evident that as the environmental conditions change, the concept of concrete durability also changes. According to the ACI-201 definition, the durability of Portland cement concrete refers to its ability to resist weathering, chemical attack, abrasion, or any other process that leads to deterioration.[1]
Compressive strength test results can serve as a method for quality control of concrete, mix design ratios, mixing method, and evaluation of the effects of admixtures on concrete.
The electrical resistance test is one of the non-destructive tests for concrete, the results of which allow experts and specialists to make decisions regarding the performance, needs, and repair and strengthening methods of concrete structures. Electrical resistance provides an estimate of the moisture content, porosity, and tortuosity of capillary pores within the concrete. This parameter is highly influenced by the quality of concrete (cement content, water-cement ratio, etc.). Ions that penetrate the concrete move and advance through the existing pores in the concrete structure. Due to the presence of ions within the concrete environment, concrete exhibits electrical conductivity, and its electrical resistivity of concrete value is directly related to its permeability and environmental conditions. Undoubtedly, the higher the permeability, the easier and faster the ions can penetrate the concrete.[2] Therefore, the higher the amount of penetrating ions, the lower the electrical resistance of concrete, and the higher the probability of rebar corrosion.
In recent years, there has been great hope for improving the durability and sustainability indices of concrete, one of which is the use of nanotechnology products.[3,4] Nanosilica is an advanced additive based on nanotechnology, designed to achieve specific and powerful concretes. Nano, in its non-crystalline state, exists as ultra-fine particles with a diameter of less than 100 nanometers, making it highly suitable as a partial replacement for cement in concrete.
In the last decade, the artificial neural network method, as a branch of artificial intelligence, has been employed in various scientific fields, including civil engineering problems, for modeling, pattern recognition, and function estimation. The artificial neural network is a method that simulates artificial

intelligence to resemble the human brain more closely and provides the ability to analyze more complex data. Many researchers have presented valuable models for estimating the behavior and indices of concrete using various mathematical techniques. One of these models is the use of artificial neural networks, which can find highly complex relationships between input and output variables without prior knowledge.[5,6,7] Mr. Tao Ji and his colleagues used neural networks to estimate different cement ratios and, through the proposed algorithm, provided a good assessment of the economic and ecological impacts of concrete.[8] Mustafa Saridemir and his colleagues performed a prediction of the compressive strength of concrete containing fly ash using artificial neural networks. They concluded that the compressive strength of fly ash concretes can be modeled in artificial neural networks and estimated without performing experiments, in a short period, and with low error.[9]

The main objective of this research is, firstly, to conduct laboratory experiments to evaluate the effect of adding nanosilica on the compressive strength and electrical resistance indices of concrete, and secondly, to model and predict these two indices using the artificial neural network method. For this purpose, 28 mix designs were prepared for water-cement ratios of 0.35, 0.40, 0.45, and 0.50 with 1%, 2%, 3%, 4%, 5%, and 6% nanosilica as a partial replacement for cement. After curing, the samples were tested at 7 and 28 days, and the results, totaling 336 data points, were considered as the network input. The input parameters of the network included water-cement ratios, percentages of nanosilica replacement for cement, and curing age, while the network output included the prediction of compressive strength and electrical resistance indices of concrete.

2 - Experimental Program

2-1 Materials Used

For concrete production, drinking water from the city of Qazvin with $6 \leq pH \leq 8$ was used according to the ASTM C94-83 standard.[10,11] The cement used was Type II Portland cement produced by the Abyek Cement Plant. Coarse aggregates (gravel) were crushed from the Shatrak Qazvin quarry, and fine aggregates (sand) were rounded from the Ghasem Qazvin quarry. Since 10 × 10 × 10 cm molds were used for casting concrete samples, the maximum size of the coarse aggregates (gravel) was limited to 19 mm (passing through the #3/4" sieve).[12] The specifications and gradation of the aggregates were in accordance with the ASTM C136-84 standard, as presented in Tables 1 and 2.[13]

Table 1 - Specifications of Aggregates Used

Aggregate	Type	Specific Gravity $\frac{gr}{cm^3}$	Water Absorption %	Maximum Aggregate Size (mm)
Gravel	Crushed	2.6	1.8	19
Sand	Natural	2.55	2.3	4.75

Table 2 - Gradation Specifications of Aggregates

Sieve Number	Nominal Maximum Aggregate Size	Percent Passing Fine Aggregate (Sand) %	Percent Passing Coarse Aggregate (Gravel) %
¾#	19 mm	-	89
½#	12.5 mm	-	46
3/8#	9.5 mm	-	20
4#	4.75 mm	94	0.002
8#	2.36 mm	78	0.0018
16#	1.18 mm	47	-
30#	600 microns	22	- -
50#	300 microns	12	-
100#	150 microns	3	-
200#	75 microns	1.5	-

The material used to partially replace cement was colloidal nanosilica. If nanosilica powder is used, a portion of it may remain unreacted in the colloidal state within the concrete. Therefore, to solve this issue, a 15% pure water-based nanosilica solution was used. The chemical structure and physical properties of the nanosilica used are presented in Tables 3 and 4.

Table 3 - Chemical Composition of Cement and Nanosilica Used (by weight percentage)

	H2O	SiC	C	SiO2	Fe2O3	AL2O3	Cao	Mgo	Na2O	K2O	P2O5	SO3

Cement	_	_	_	21.5	4	5.2	65	1.8	0.58	0.58	_	1.8
Nanosilica	80	5	3	14.5	0.87	1.3	0.49	0.97	0.31	1	0.16	0.1

Table 4 - Physical Properties of Nanosilica Used

Average Particle Size	Color	Physical State	Density	*PH*	SiO_2 Content (%)
Less than 30 nm	Transparent Milky	Liquid	1.3 $^{gr}/_{cm^3}$	9.5~10.4	13~14.6

It should be noted that due to the extremely high water absorption property of nanosilica when added to the concrete mixture, the use of a strong superplasticizer is mandatory. Therefore, in this research, a polycarboxylate-based superplasticizer produced by Abadgaran Company with the commercial name ABAPLAST WR-4610, Type "F" was used.[14] This admixture complies with ASTM C1017, ASTM C494 - TYPE-F, EN 934-2, and ISIRI-2930 Table 3&4 standards.[15-16-17-18]
Additionally, to achieve consistent compaction energy in casting all samples, the slump of the samples was maintained within a fixed range for each water-cement ratio. This was accomplished by adjusting the amount of superplasticizer used. The physical properties and chemical composition of the concrete superplasticizer are presented in Table 5.

Table 5 - Physical Properties of Superplasticizer Used

Color	**Physical State**	**Density**	**PH**	**Chloride Ion**	**Commercial Name**	**Manufacturer**
Light Honey	Concentrated Liquid	$^{gr}/_{cm^3}$ 1.42	6.5	None	ABAPLASTWR-4610	Abadgaran

2-2 Mix Design Table

According to Table 6, the type of cement and aggregates, as well as the aggregate content in the concrete, remained constant. The water-to-cement ratio (w/c), the weight percentage of nanosilica, and the curing age of the concrete were considered as variables. The mix design method used in this research was based on the recommended procedure in ASTM C305, with slight modifications due to the use of superplasticizer and nanosilica admixtures.[19-20]

Table 6 - Constant and Variable Parameters in the Mix Design

	Item	Variable	Constant
1	Type and Nature of Aggregates	-	✓
2	Amount of Aggregates	-	✓
3	Type of Cement	-	✓
4	Water-to-Cement Ratio	✓	-
5	Percentage of Nanosilica Replacement	✓	-
6	Specimen Curing Age	✓	-

For the material mix design, the aggregates (gravel and sand) were first dry-mixed in the concrete mixer for two minutes. Then, approximately 5% of the mix water was added to the mixer, and the aggregates were soaked for two minutes. After that, the required cement was gradually added to the wet aggregates. The nanosilica liquid was then gently added over one minute to the rotating materials inside the concrete mixer. In the final step, the superplasticizer was added to the mix. After adding all materials and admixtures to the concrete mixer, the mixer drum rotated at a 45-degree angle for approximately four minutes to ensure that all materials and aggregates were thoroughly combined, resulting in a homogeneous mixture. In this research, a total of 28 mix designs were used. The complete mix design specifications are detailed in the following table.

Table 7 - Mix Design Quantities

Mix No.	Mix Name	$\frac{W}{C}$	$\frac{kg}{m^3}$ Cement	Gravel $\frac{kg}{m^3}$	$\frac{kg}{m^3}$ Sand	Nanosilica Replacement (%)	Superplasticizer $\frac{kg}{m^3}$	Slump (cm)
1	0.35 -N -0	0.35	400	1000	800	0	0	1.5
2	0.35-N-1	0.35	396	1000	800	1	1.9	5
3	0.35-N-2	0.35	392	1000	800	2	3	3.5
4	0.35-N-3	0.35	388	1000	800	3	4	4
5	0.35-N-4	0.35	384	1000	800	4	5.8	4.5
6	0.35-N-5	0.35	380	1000	800	5	8	4
7	0.35 -N -6	0.35	376	1000	800	6	9.6	3
8	0.40-N -0	0.40	400	1000	800	0	0	3.5
9	0.40-N-1	0.40	396	1000	800	1	1.65	5
10	0.40-N-2	0.40	392	1000	800	2	2.35	4
11	0.40-N-3	0.40	388	1000	800	3	2.8	5
12	0.40-N-4	0.40	384	1000	800	4	3.85	5
13	0.40-N-5	0.40	380	1000	800	5	6	4.5
14	0.40-N-6	0.40	376	1000	800	6	8.9	4
15	0.45-N -0	0.45	400	1000	800	0	0	4.5
16	0.45-N-1	0.45	396	1000	800	1	1	5
17	0.45-N-2	0.45	392	1000	800	2	1.53	4.5
18	0.45-N-3	0.45	388	1000	800	3	2.3	5
19	0.45-N-4	0.45	384	1000	800	4	3.54	5
20	0.45 -N -5	0.45	380	1000	800	5	4.9	6
21	0.45-N-6	0.45	376	1000	800	6	8.3	4
22	0.50-N-0	0.50	400	1000	800	0	0	10.5
23	0.50-N-1	0.50	396	1000	800	1	1	8
24	0.50-N-2	0.50	392	1000	800	2	1.08	8
25	0.50-N-3	0.50	388	1000	800	3	1.85	7
26	0.50-N-4	0.50	384	1000	800	4	2.93	8
27	0.50-N-5	0.50	380	1000	800	5	3.6	6.5
28	0.50-N-6	0.50	376	1000	800	6	5.50	9

2-3 - Specimen Preparation and Casting

To improve the quality of the concrete specimens, entrapped air was removed from the fresh concrete using a vibrating table and plastic mallet strikes on the mold. After 24 hours of setting, the specimens were demolded and cured in a water tank until the ages of 7 and 28 days.[21,22]

2-4 - Test Details and Results

2-4-1 Compressive Strength Test

After the concrete specimens reached the desired age, they were removed from the water tank and tested using a hydraulic compression testing machine according to the BS:1881–part 116 standard.[23] For greater accuracy and reduced test error, it is recommended to ensure that the upper and lower platens of the hydraulic jack are leveled before starting the test and that the center of the cubic specimen is precisely positioned at the center of the spherical upper and lower platens to apply the load perpendicularly to the concrete surface. Otherwise, in addition to the uniaxial compression, lateral shear stress will also be induced. The load is applied at a constant stress rate of 0.2 to 0.4 MPa/second.[24]

Figure 1 - Hydraulic Compression Testing Machine

2-4-2 Electrical Resistance Test

This test was conducted based on the ASTM C1760-12 standard using the "two-point" method.[25] First, the specimen was removed from the water and dried with a cotton cloth. Then, by applying cement paste on the top and bottom faces, as shown in Figure 2, the cubic specimen was placed between two copper metal plates and an electric current was passed through these plates to measure the electrical resistance.

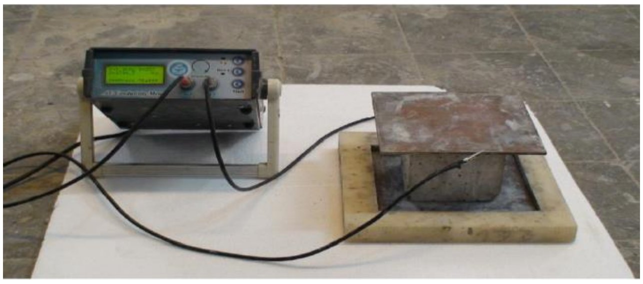


Figure 2 - Electrical Resistance Testing Device (Two-Point Method)

After determining the electric current, the specific electrical resistance was calculated using the following equation (1):

$$\rho = R\frac{LA}{L} \quad (1)$$

Where ρ is the specific resistance (ohm-cm), R is the actual resistance (ohm), A is the specimen surface area (cm2), and L is the specimen length (cm).

According to the ACI 222 standard, the corrosion rate is classified into four categories based on the electrical resistance, as shown in Table 8.[26]

Table 8 - Corrosion Rating Based on Concrete Electrical Resistance

Specific Electrical Resistance (kohm-cm)	**Corrosion Rate**
5>	Very High
5-10	High
10-20	Moderate to Low
20<	Negligible

2-5 Test Results

2-5-1 Compressive Strength Test

The compressive strength test results are the average of tests performed on three cubic specimens, as shown in Figures 3-1 to 3-6.

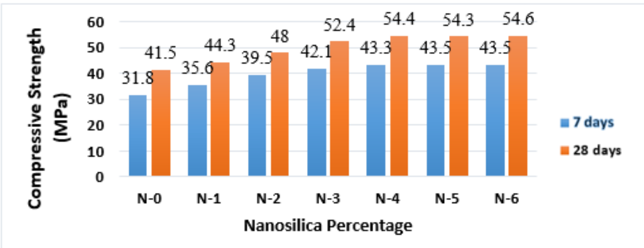


Figure (3-1) Compressive Strength Chart for Mix Design (w/c=0.35)

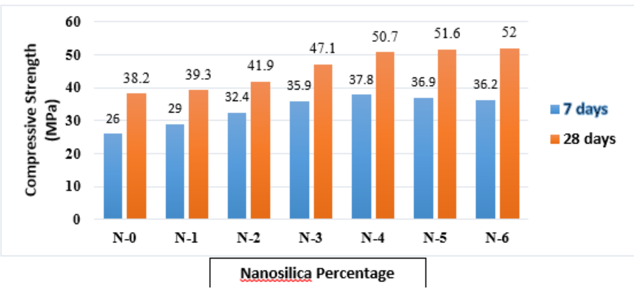


Figure (3-2) Compressive Strength Chart for Mix Design (w/c=0.4)

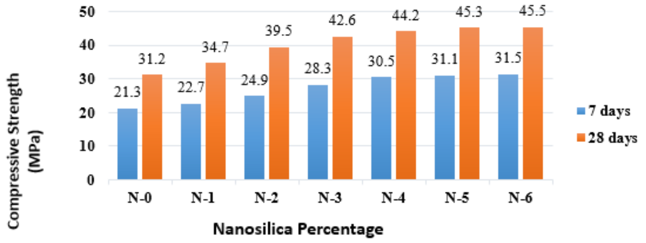


Figure (3-3) Compressive Strength Chart for Mix Design (w/c=0.45)

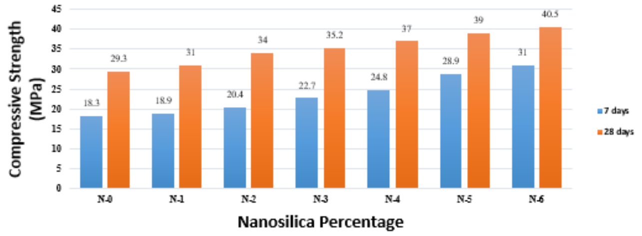


Figure (3-4) Compressive Strength Chart for Mix Design (w/c=0.5)

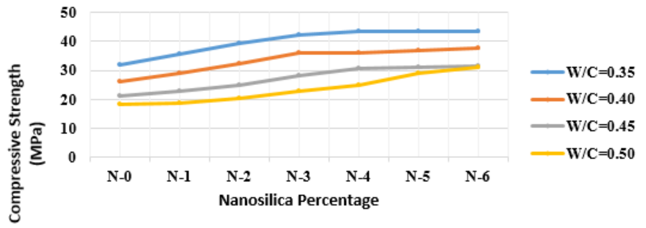


Figure (3-5) Chart of 7-day Compressive Strength Change Rate for Different Water-Cement Ratios

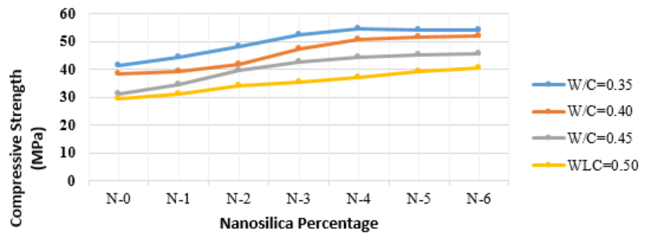


Figure (3-6) Chart of 28-day Compressive Strength Change Rate for Different Water-Cement Ratios

2-5-2 Electrical Resistance Test

The electrical resistance test results are the average of tests performed on three cubic specimens, as shown in Figures 4-1 to 4-8.

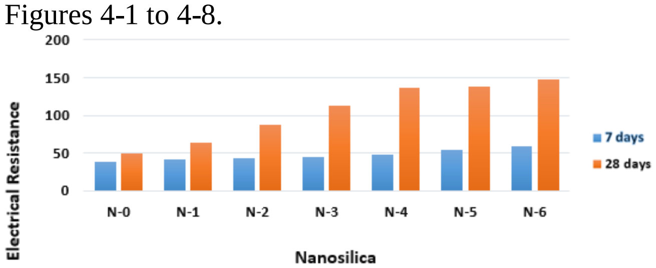


Figure (4-1) Electrical Resistance Chart for (w/c=0.35)

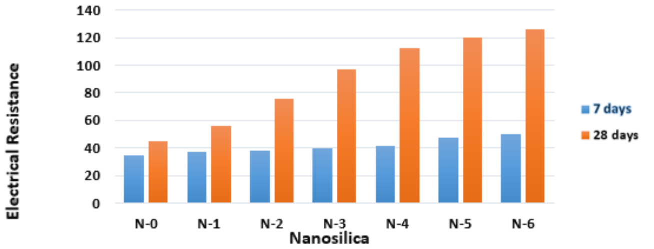


Figure (4-2) Electrical Resistance Chart for (w/c=0.40)

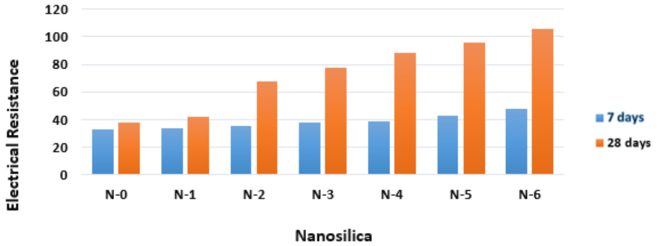


Figure (4-3) Electrical Resistance Chart for (w/c=0.45)

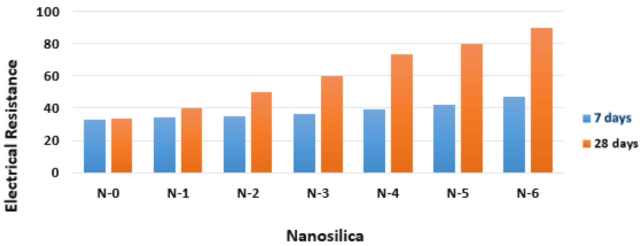


Figure (4-4) Electrical Resistance Chart for (w/c=0.50)

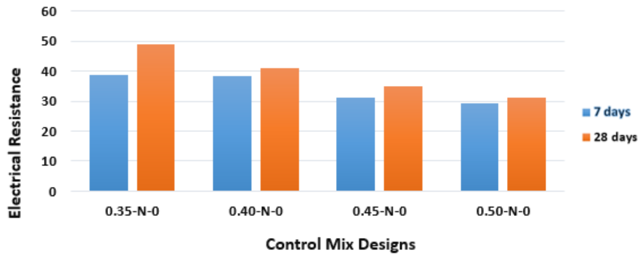


Figure (4-5) Electrical Resistance Chart for Control Mix Designs
Electrical Resistance

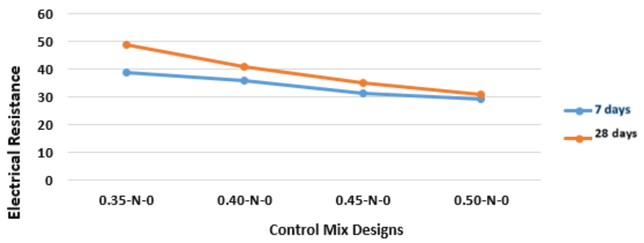


Figure (4-6) Chart of Electrical Resistance Change Rate for Control Mix Designs

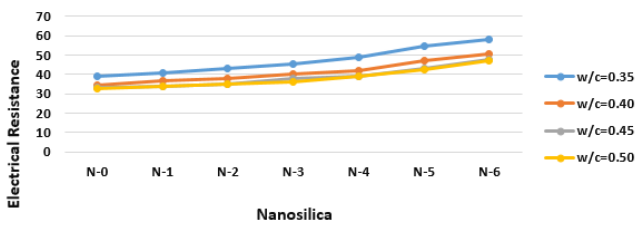


Figure (4-7) Chart of 7-day Electrical Resistance Change Rate for Different Water-Cement Ratios

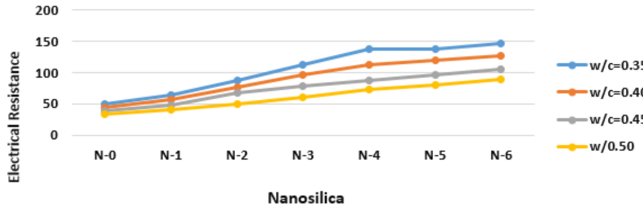


Figure (4-8) Chart of 28-day Electrical Resistance Change Rate for Different Water-Cement Ratios

3. Artificial Neural Networks

The computational method, as a branch of artificial intelligence knowledge, is somewhat inspired by the way the human brain's neural system processes data and information for learning, built upon interconnected multiple processing units. The network consists of a desired number of processing units (neurons, cells, nodes) arranged in layers, which relate the input set to the output set. Neurons naturally connect in a specific way to form a neural network. The way neurons connect can create either a single-layer or multi-layer network.[27,28]

3-1. Multi-Layer Perceptron (MLP) Networks

Multi-layer networks are composed of an input layer, an output layer, and one or more hidden layers in between that are not directly connected to the input data and output results. The input layer is solely responsible for distril 7 days input values to the network and does no e input signals. The output layer represents 28 days se to the input signals and outputs. The hidden layers are responsible for connecting the input layer to the output layer. With these hidden layers, the network can extract non-linear relationships from the data presented to the network. Neurons in the multi-layer neural network are used to minimize the error percentage for the test and training datasets.[29]

3-2. Backpropagation Training Algorithm

The "backpropagation" algorithm has been used as one of the most well-known learning algorithms. Network training is essentially done by presenting sets of sample input patterns and their corresponding output values. The neural network learns what to compute through the weights of the interconnected neurons.

7 days

3-3. Investigating the 28 days Modeling Process in this Research

In this research, the 28 days creating the neural network model was not obtained from the results of previous researchers' experiments. Instead, as shown in the algorithm in Figure 5, the input data for training the network was derived from conducting the relevant experiments in the laboratory and their resulting data.

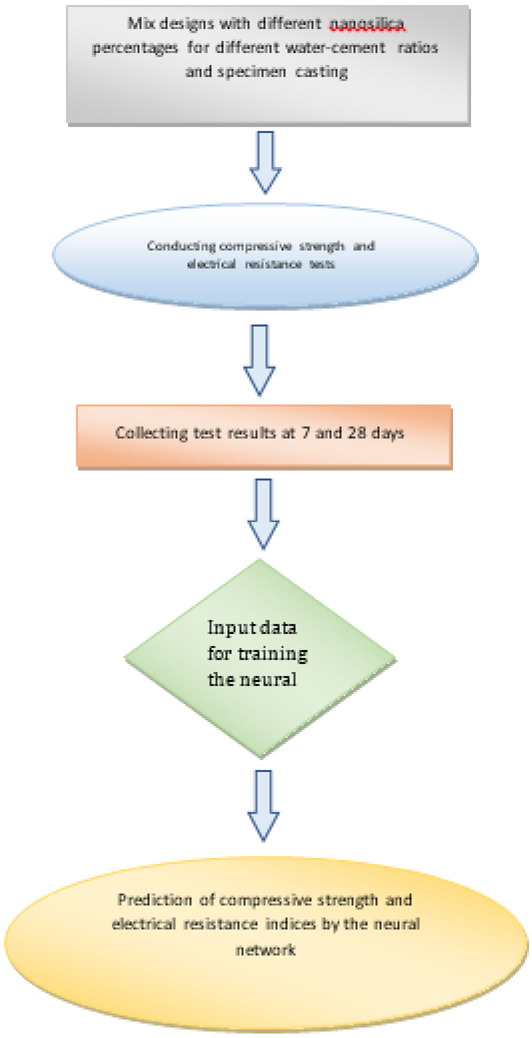


Figure 5 - Algorithm of Network Modeling Process in this Research

The inputs to the present neural network, considering their significant impact on the compressive strength and electrical resistance indices of concrete, are considered network variables, which include: the water-cement ratio, percentage of nanosilica replacement for cement, specimen age, and the network output (objective function) includes: compressive strength and electrical resistance. The minimum and maximum values of the input and output of the modeled network are described in the following table.

Table 9 - Minimum and Maximum Values of Network Input and Output

Data	Component	Minimum	Maximum
Network Input	Water-Cement Ratio	0.35	0.50
	Nanosilica Percentage (Cement Replacement) %	0	6
	Concrete Curing Age (days)	7	28
	7-day Compressive Strength (MPa)	18.3	43.5
	28-day Compressive Strength (MPa)	24.5	54.3
Network Output	7-day Electrical Resistance (kohm-cm)	32.5	58.3
	28-day Electrical Resistance (kohm-cm)	33.4	137

The network data was divided into training and testing sets. The total number of input samples was 336, with 70% of the data allocated for network training, 15% for network validation, and 15% for network testing. Selecting the number of nodes (neurons) in the hidden layer is one of the most challenging aspects of the overall network development process. Unfortunately, there are no definitive guidelines for achieving this goal, so it must be done through a trial-and-error approach. Neurons in the multi-layer neural network are used to minimize the error percentage for the test and training sets. In this research, through the "trial-and-error" method, the optimal state was achieved with five neurons in the hidden layer.[30] Increasing the number of neurons in the layers enhances the network's ability to learn and predict the non-linear behavior of the model, but it also increases the amount and time of calculations, and there is a risk of the network experiencing overfitting. To avoid the mentioned problems, the minimum number of neurons that can predict with satisfactory accuracy should be used.

The neural network in this research, a type of "multi-layer feedforward" (MLP), was modeled using MATLAB software. The number of neurons in the input and output layers was assumed to be three and five, respectively, corresponding to the number of inputs and outputs. However, the number of neurons in the hidden layer was gradually increased through trial and error until the sum of the mean squared error reached its minimum value. In this regard, up to five neurons, there was a decreasing trend in error, but with a further increase, the number of neurons in this layer did not practically show a further reduction in the network performance error; it only increased the computation time. Therefore, five neurons in the hidden layer were considered as the optimal state for the mentioned network. The hidden layer transfer function is the tangent sigmoid, and the output transfer function is linear. The role of the transfer function is to modulate the measured sum of the inputs. After the trial-and-error process, the structure and general specifications of the optimized neural network are as follows in Table 10.

Table 10 - General Specifications of the Optimized Neural Network

Type	Training Algorithm	Transfer Functions		Number of Hidden Layers	Number of Neurons			Network Performance Index (Error Calculation Function)
		Hidden Layer	Output Layer		Input Layer	Hidden Layer	Output Layer	

Multi-layer MLP	Backpropagation - Supervised Feed Forward	(Tangent	Linear	One Layer	3	5	2	Mean Squared Error (MSE)

Based on the table, the network with five neurons and a non-linear sigmoid transfer function in one hidden layer, as well as one neuron and a linear transfer function in the output layer, estimates the best results. The schematic model of this network is presented in Figure 6.

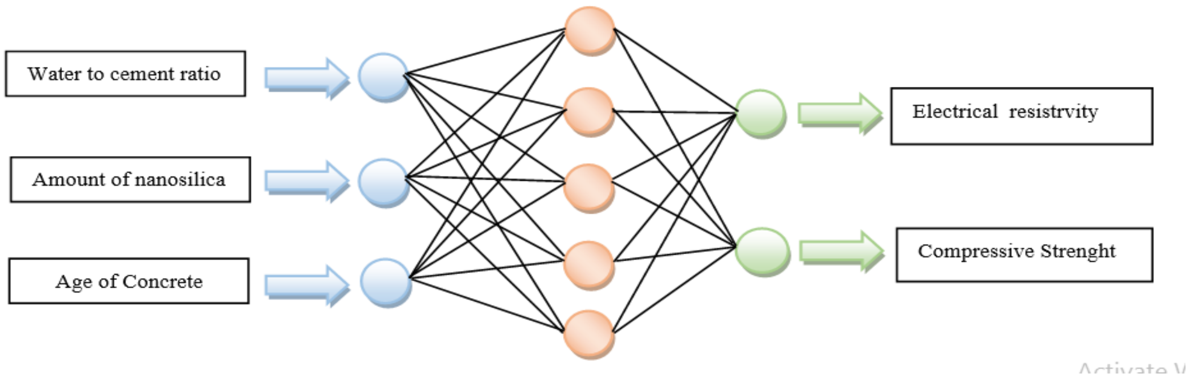


Figure 6 - Optimal Network Model for Estimating Concrete Compressive Strength and Electrical Resistance

6-4 - Presentation and Analysis of Tested Neural Network Results

To calculate the network performance, the mean squared error (MSE) index was used, which is based on equation (2) and includes three computational operations: a) the system output error, b) squaring the system output error, and c) averaging the sum of all errors:

(2)

$$MSE = (1/p) \times \sum_j (t_j - s_j)^2$$

As shown in the results of the charts in Figure 7, the regression correlation coefficient (R) for the training set is 0.99999, for the test set is 0.99078, and for the entire dataset is 0.99997. The network's accuracy in modeling the training, test, and overall data sets is close, indicating the proposed neural network's suitable modeling capability, proper training, and absence of overfitting.

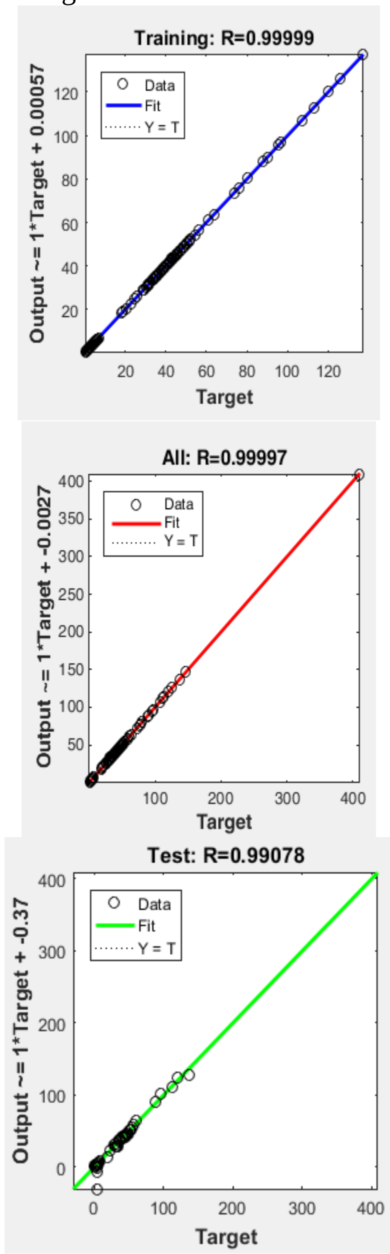


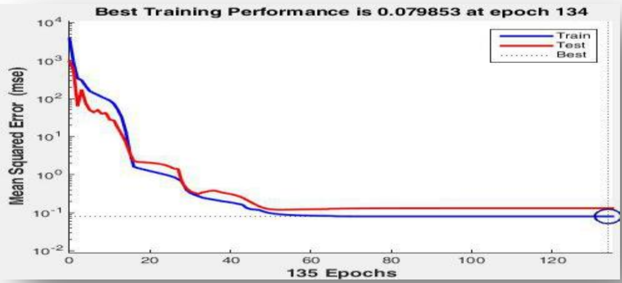
Figure 7 - Charts comparing predicted durability indices with actual durability indices (entire data set, validation, training)

The results of the network's optimal performance are summarized in Table 11.

Table 11 - Optimal Network Performance Results

Error Function (Cost Function)	R - Model Prediction Accuracy		
	Entire Data Set	Validation Data Set	Training Data Set
0.079853	0.99997	0.99999	0.99078

According to the network performance chart in Figure 8, after 134 cycles (epochs), with the convergence of the training and validation curves, the network achieves its best training performance, and the error function reaches a minimum constant value of



0.079853.

Figure 8 - Network Performance Chart

7. Conclusion

● Nanosilica, as a substitute for cement in concrete, improves the properties of concrete, including increasing compressive strength and electrical resistance. In other words, the use of nanomaterials has had an effective and remarkable impact on concrete technology, and nanoparticles such as nanosilica, due to their high energy surface, readily react with other external atoms, which intensifies their chemical reaction.

● The optimum amount of nanosilica consumption for improving compressive strength is estimated to be around 5%, such that adding more nanosilica will no longer result in a noticeable increase in compressive strength.

● The use of a combination of a plasticizer and nanosilica generally increases electrical resistance, with the rate of increase being slower at 7 days but significantly higher at 28 days. This is because concrete performs most of its pozzolanic reaction by the age of 28 days, and its effect is to fill voids and consequently increase the density of the cement gel.

● By comparing the control samples, we find that decreasing the water-to-cement ratio increases both compressive strength and electrical resistance, and vice versa. The reason for this is that reducing the water-to-cement ratio decreases the amount of voids, resulting in denser concrete.

● To evaluate the network's performance, the correlation coefficient (R) statistical parameter was used. After training the network with high accuracy, it can predict for both the training data set and the entire data set, indicating proper training of the neural network and suitable selection of training parameters.

● The neural network's prediction results indicate that ANN is a model for predicting compressive strength and electrical resistance with low error.

● Considering the repetitive and time-consuming laboratory operations, the use of artificial neural network methods can provide the ability to predict compressive strength and electrical resistance, while saving time and cost by avoiding repetitive and time-consuming operations.

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