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USING THE ARTIFICIAL NEURAL NETWORKS FOR PREDICTING COMPRESSIVE STRENGTH OF NORMALLY CONCRETES

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ABSTRACT

In this study Artificial Neural Networks (ANNs) models were developed for predicting the compressive strength, at the age of 28 days, of normally concretes. The experimental results used to construct the models were gathered from laboratory of Isra University - Amman in 2019. Total of 15 experimental design used for modeling ANN models. 80% in the training set, and 10% in the testing set, and 10% in the validation set. To construct the model, three input parameters were used to achieve one output parameter, referred to as the compressive strength of normally concrete. The results obtained in both, the training and testing phases strongly show the potential use of ANN to predict 28 days' compressive strength of normally concretes with average accuracy 90% and correlation coefficient 95%.

Key words: Normally Concrete, Artificial neural network, Model.

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1. INTRODUCTION

Conventional concrete is a mixture of cement, water, and coarse and fine aggregates. Supplementary components such as chemical and mineral admixtures may be added to the basic concrete ingredients to enhance its properties in fresh or hardened state. The procedure of selecting appropriate ingredients for concrete and its relative amount with the aim of producing concrete of obligatory strength, workability, and durability as cost-spinning as possible is termed mix design.

The Compressive Strength of concrete determines the quality of concrete. This is generally determined by a standard crushing test on a concrete cylinder. This requires engineers to build small concrete cylinders with different combinations of raw materials and test these cylinders for strength variations with a change in each raw material. The recommended wait time for testing the cylinder is 28 days to ensure correct results. This consumes a lot of time and requires a lot of labor to prepare different prototypes and test them.

In recent years, many researchers have been working on developing accurate concrete compressive strength prediction models [*I-Cheng Yeh. 1998, Ahsanul et al, 201*.].

The prediction of compressive strength of concrete has great connotation, if it is brisk and consistent because it offers an option to do the essential modification on the mix proportion used to avoid circumstances where concrete does not attain the mandatory design strength or by avoiding concrete that is gratuitously sturdy and also for more economic use of raw material and fewer construction failures, hence reducing construction cost *(I-Cheng Yeh. 1998)*

One way of reducing the wait time and reducing the number of combinations to try is to make use of ANN models. But, to design such models it has to know the relations between all the raw materials and how one material affects the strength. It is possible to derive mathematical equations, but it cannot expect the relations to be same in real-world *(Ahsanul et al, 2013)*.

2. ARTIFICIAL NEURAL NETWORK: BACKGROUND

According to *Rumelhart et al. (1986),* there are eight components of a parallel distributed processing model such as the neural network. These eight components are the processing units or neurons, the activation function, the output function, the connectivity pattern, the propagation rule, the activation rule, the learning rule and the environment in which the system operates. Neural networks are a series of interconnected artificial neurons which are trained using available data to understand the underlying pattern. They consist of a series of layers with a number of processing elements within each layer. The layers can be divided into input layer, hidden layer and output layer. Information is provided to the network through the input layer, the hidden layer processes the information by applying and adjusting the weights and biases and the output layer gives the output *(Karna and Breen 1989).* Each layer may have a number of processing units called neurons. The inputs are weighted to determine the amount of influence it has on the output *(Karna and Breen 1989),* input signals with larger weights influence the neurons to a higher extend. An activation function is then applied to the weighted inputs, to produce an output signal by transforming the input. The input can be a single node or it may be multiple nodes depicting different parameters where each of the input nodes acts as an input to the hidden layer. The hidden layer consists of a number of neurons/nodes which calculate the weighted sum of the input data.*(Jaber et al, 2020)*

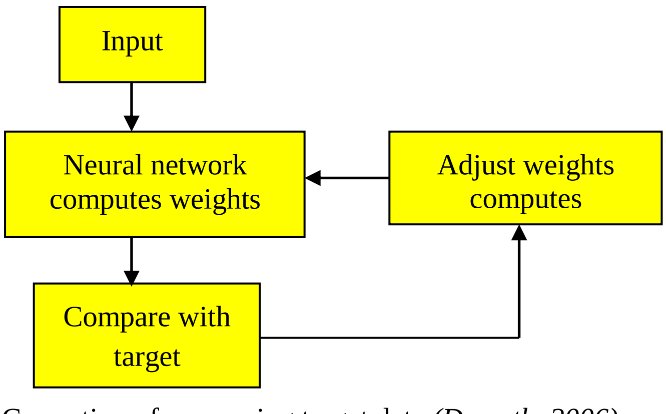

Figure 1 Correction of error using target data *(Demuth, 2006)*

Figure (1) shows how neural network adjusts the weights and biases by comparing the output with the target. The weights are not fixed but they change over time by gaining experience after several iterations *(Rumelhart et al. 1986)*. Artificial neural networks are used in pattern classification, clustering/categorizing, function approximation, predicting, optimization, control and content-addressable memory *(Jain et al. 1996) (Al-Zwainy, 2009).*

Back-propagation algorithm is simple and effective in solving large and difficult problems *(Alavala, 2008)*. Thus, it is used in learning process of the model. It consists of two phases: forward pass and backward pass *(Beale and Jackson, 1990)*. In forward pass, the parameters of the input variables pass though the functions of the network and an output data is produced, in the end. In backward pass, firstly the error is calculated by subtracting the actual output from desired output. Then, it is propagated backward through the network. The weights are adjusted during the backward pass *(Ayed, 1997)*. This process optimizes the weight parameters of the model, decrease the error value and increase the prediction power of the ANN model.

There are methods that significantly improve the back-propagation algorithm's performance *(Haykin, 1999)(Ibraheem, 2020):*

- Sequential versus batch update: When the training data set is large and highly redundant, sequential mode of back propagation learning could be preferred than the batch mode of the algorithm.
- Maximizing information content: The training data should be strong enough to maximize the learning rate or the model. There are two ways to form such strong training information; using data that is having the largest training error, and using data that is oppositely different the other data used before.
- Activation function: Using sigmoid activation function increases the learning ability of the model. Applying hyperbolic tangent, a nonlinear sigmoid antisymmetric activation function of sigmoid nonlinearity, is popular in this way.
- Learning from hints: Learning from a set of training examples deals with an unknown input-output mapping function.
- Learning rates: Learning rate values are important for the network in learning process. Neurons with many inputs should have smaller learning rate parameter, or vice versa.

3. IDENTIFICATION OF ANN MODEL VARIABLES

The neural network application for deflection estimation is an example of causal forecasting. This type of forecasting considers a number of variables that affect the variable to be predicted. This type of forecasting is more powerful than the traditional methods. The purpose of deflection estimation is to predict or estimate the Compressive Strength from known or assumed values of other variables related to it. One of the most important tasks of this objective is to determine which variables are important indicators. Once the appropriate variables have been determined, the Compressive Strength estimation can be performed either using a neural network or any other tool.

This research describes the development of neural network models for Compressive Strength based on historical projects data. The initial impetus for the research was the paucity of data available that can provide reliable information about the Compressive Strength. The data used to develop the neural network model of estimation of the Compressive Strength were past projects contract data from laboratory of Isra University - Amman in 2019.

The model input variables for this model are consisting of sex variables (i.e. T1, T2, and T3). There is one type of variables that might affect the estimation of Compressive Strength objective variables only.

Objective variables: This type comprised eleven variables, as the following

T1	W/c-ratio
T2	Mix design (Cement : sand : Gravel)
T3	Cement content (C) kg/m3

Subjective variables: This type comprised nine variables, as the following

Y1	compressive strength ,28 days, (MPa)

The experimental data used for the prediction of concrete compressive strength in the present study have been taken from the research work conducted by Isra University - Amman in 2019. For generating a trustworthy information bank on concrete compressive strength, variation in The dataset consists of 1030 instances with 9 attributes and has no missing values. There are 8 input variables and 1 output variable. Seven input variables represent the amount of raw material (measured in kg/m^3) and one represents Age (in Days). The target variable is Concrete Compressive Strength measured in (MPa — Mega Pascal) at 28 days as shown in Table 1.

Table 1 Experimental data

No.	W/c-ratio	Mix design (Cement : sand : Gravel)	Cement content (C) kg/m^3	compressive strength 28 (d) MPa
1	0.50	1 : 1.60 : 3.00	385.00	44.43
2	0.52	1 : 1.34 : 2.28	410.00	35.78
3	0.55	1 : 1.45 : 2.89	420.00	46.26
4	0.40	1 : 1.30 : 2.60	435.00	44.15
5	0.42	1 : 1.40 : 2.88	445.00	48.43
6	0.44	1 : 1.24 : 2.38	455.00	46.62
7	0.46	1 : 1.35 : 2.64	460.00	56.41
8	0.48	1 : 1.25 : 2.29	465.00	57.15
9	0.49	1 : 1.39 : 2.56	470.00	38.91
10	0.53	1 : 1.48 : 3.45	375.00	44.00
11	0.56	1 : 1.53 : 2.52	400.00	43.00
12	0.59	1 : 1.64 : 2.69	410.00	45.50
13	0.47	1 : 1.78 : 2.78	420.00	46.70
14	0.45	1 : 1.89 : 2.87	425.00	46.50
15	0.53	1 : 1.91 : 2.85	430.00	45.00

4. DEVELOPMENT OF ANN MODEL

In an effort to develop a more realistic deflection model, this study attempts to overcome some of Neural Network drawbacks, and presents it as a simple and transparent approach for use in construction. Accordingly, a three-layer Neural Network has been simulated on a (NEUFRAME, Version 4) program that is easy to use, transparent, and customary to many practitioners in construction. The simulation of Neural Networks on a NEUFRAME program presents its underlying mathematical formulas in a simple and fully controllable form. . Figure (2) shows the scheme of the NEUFRAME 4 program which is built to determine the relationship between the independent variables (inputs) and the dependent variable (output).

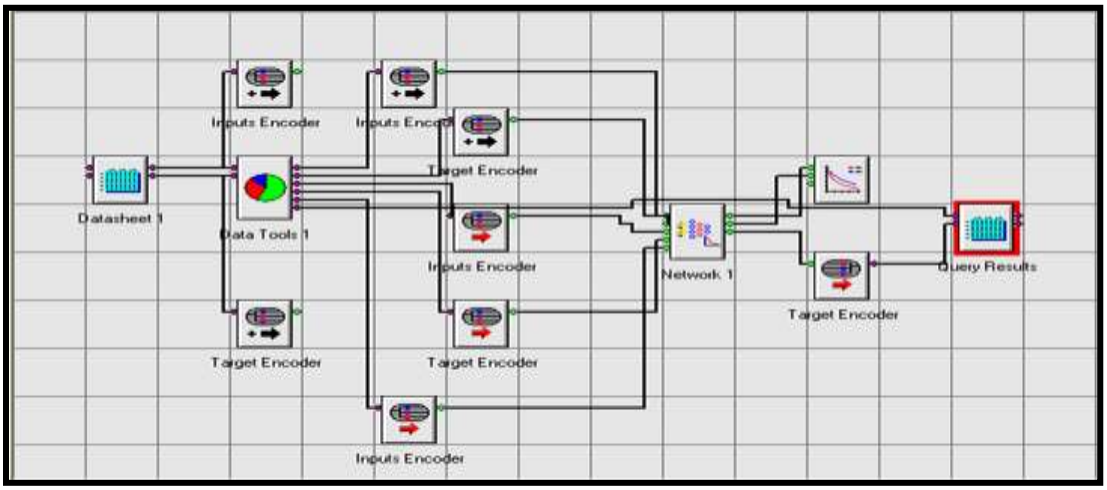

Figure 2 Graphing Component of NEUFRAM 4 Program

The next step in the development of ANN models is the division of the available data into their subsets, training, testing and validation sets. trail–and-error process was used to select the best division, by using *Neuframe* software. It can be seen that the best data subsets division is (80%- 10% -10%) according to lowest testing and training error coupled (6.4%) and (5.8%) with highest correlation coefficient of validation set (95%). Thus, this division was used in this model

Table 2 Effect of data division on performance of ANNs

Data Division			**training error%**	**testing error%**	**coefficient correlation(r)%**
Training%	**Testing%**	**Querying%**			
80	10	10	5.8	6.4	95
80	6	14	12.2	9.5	92
70	10	20	12.5	11.01	91
70	12	18	13.1	11.12	91
75	24	1	14.6	10.22	92
65	20	15	14.7	11.33	92
65	15	20	15.7	12.34	90
60	25	15	15.53	13.45	89
60	10	30	15.78	13.55	88
60	30	10	15.90	14.66	88

The effects of using different choices for divisions (i.e. striped, blocked, and random) were investigated and it was shown in table (3), it can be seen that the performance of ANNs model was relatively insensitive to the method of division. The better performance was obtained when the striped division was used, according to lowest testing (6.4%) and training error (5.8%) coupled with highest correlation coefficient of validation set (95%).

Table 3 Effects of method division on ANNs performance

Data Division%			**choices of division**	**training error%**	**testing error%**	**coefficient correlation(r)%**
Training	**Testing**	**Querying**				
80	10	10	Striped	5.8	6.4	95
80	10	10	Blocked	8.77	9.10	94.50
80	10	10	Random	8.34	9.88	94.44

One of the most important and difficult tasks in the development of ANN models is the determination of the model architecture (i.e. the number and connectivity of the hidden layer nodes). The network of (Model C-1) is set to one hidden layer with default parameters of software (learning rate equals to 0.2 and momentum term equals to 0.8). A number of trials were carried out with one hidden layer and 1, 2, 3, 4, 5, 6, and 7 hidden layer nodes (2I+1) (where I the number of input nodes) and the results are summarized in table (4). It can be seen that the Model 1 with (93.4%). It is believed that the network with one hidden node is considered optimal. Thus, it was chosen in this model.

Table 4 Effects no. of nodes on ANNs performance (Model 2)

<table>
<tr><th>Model No.</th><th>Parameters Effect</th><th>No. of Nodes</th><th>training error%</th><th>testing error%</th><th>coefficient correlation(r)%</th></tr>
<tr><td>C-1</td><td rowspan="7">choices of division
(Striped)

Learning Rate
(0.2)

Momentum Term
(0.8)

Transfer function in hidden layer
(Sigmoid)

Transfer function in output layer
(Sigmoid)</td><td>1</td><td>5.8</td><td>6.4</td><td>95</td></tr>
<tr><td>C-2</td><td>2</td><td>6.6</td><td>6.9</td><td>94.56</td></tr>
<tr><td>C -3</td><td>3</td><td>7.9</td><td>6,9</td><td>94.10</td></tr>
<tr><td>C -4</td><td>4</td><td>8.8</td><td>7.1</td><td>93.45</td></tr>
<tr><td>C -5</td><td>5</td><td>9.4</td><td>7,3</td><td>92.56</td></tr>
<tr><td>C -6</td><td>6</td><td>9.6</td><td>7.3</td><td>91.00</td></tr>
<tr><td>C -7</td><td>7</td><td>9.7</td><td>7.6</td><td>90.56</td></tr>
</table>

The small number of connection weights obtained by *Neuframe* for the optimal ANNs model (Model C-1) enables the network to be translated into relatively simple formula. To demonstrate this, the structure of the ANNs model is shown in figure. (3), while as connection weights and threshold levels (bias) are summarized in table (5).

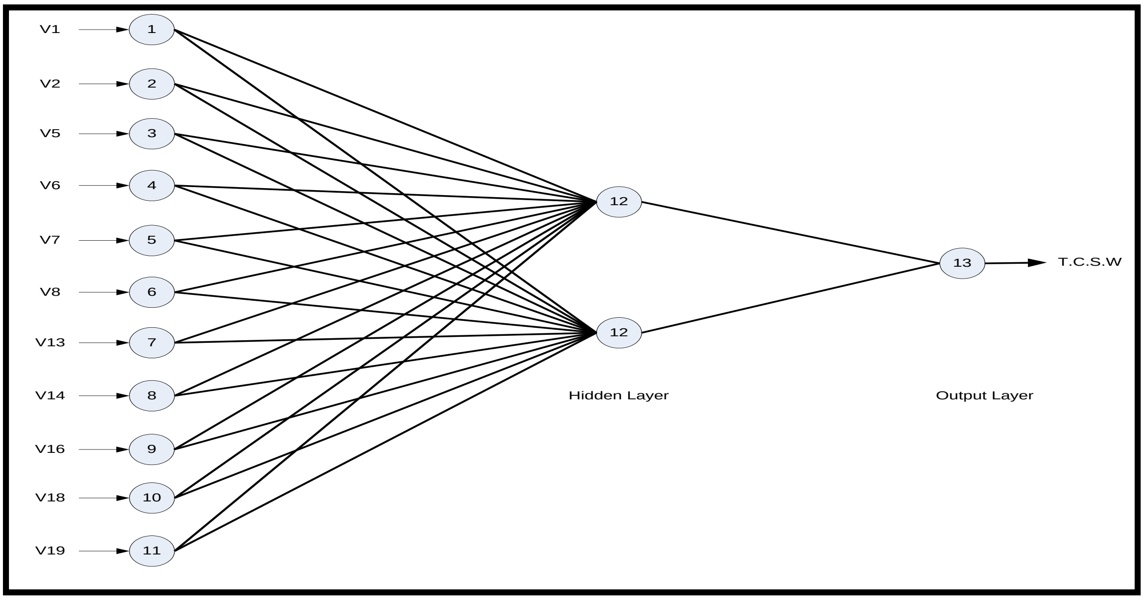

Figure 3 Structure of the ANNs optimal model (D-1)

Table 5 Weights and threshold levels for the ANNs optimal model (Model C-1).

w_{ji} (weight from node i in the input layer to node j in the hidden layer)			
i=1	i=2	i=3	i=4
0.6788	0.8989	0.9877	-2.65
Hidden layer threshold θ_j			Output layer threshold θ_j
0.56			1.66

Using the connection weights and the threshold levels shown in Table (6), the predicted of total cost can be expressed as follows:

$$Y = \text{compressive strength} = \frac{2.544}{1+e^{(-1.66+0.56\tanh x_1)}} + 35.87 \qquad (5)$$

And

$$X_1 = 0.6788\ T1 + 0.8989\ T2 + 0.9877\ T3 \qquad (6)$$

5. VALIDITY OF THE ANN MODEL

The statistical measures used to measure the performance of the models included:

- Mean Absolute Percentage Error (MAPE),

$$MAPE = \left(\sum_{i=1}^{n} \frac{|A-E|}{A} * 100\% \right) \Big/ n \qquad (10)$$

- Average Accuracy Percentage (AA %)

$$AA\% = 100\% - MAPE \qquad (11)$$

- The Coefficient of Determination (R^2);
- The Coefficient of Correlation (R);

The coefficient of determination measures how well the model outputs match the target value. The MAPE and percentage RMSE are measures of the average error.

The results of the comparative study are given in Table (9). The MAPE and Average Accuracy Percentage generated by ANN model (C-1) were found to be 10% and 90% respectively. Therefore, it can be concluded that ANN model shows a very good agreement with the actual information.

Table 6 Results of the Comparative Study

Description	ANN for Model
MAPE	10.00%
AA %	90.00%
R	95.00%
R^2	90.25%

It is clear from figure (8). the generalization capability of ANNs techniques using the validation data set. The coefficient of determination (R^2) is (90.25%), therefore it can be concluded that ANNs model show very good agreement with the actual measurements. as shown in figure (8).

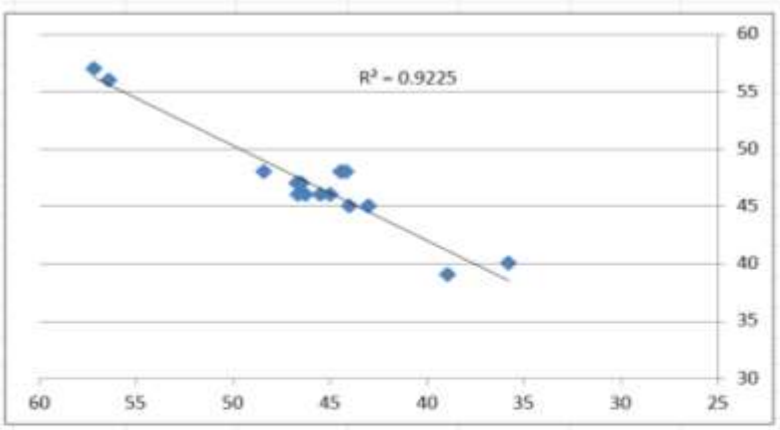

Figure 8 Comparison of predicted and observed deflections for validation data

6. CONCLUSION

In this study, one hidden layer with three hidden node for model (C-1) is practically enough for the neural network analysis. The experimental results used to construct the models were gathered from laboratory of Isra University - Amman in 2019. Total of 15 experimental design used for modeling ANN models. 80% in the training set, and 10% in the testing set, and 10% in the validation set. To construct the model, three input parameters were used to achieve one output parameter, referred to as the compressive strength of normally concrete. The results obtained in both, the training and testing phases strongly show the potential use of ANN to predict 28 days compressive strength of normally concretes with average accuracy 90% and correlation coefficient 95%. The findings show that one ANN model is able to learn the cause-effect relationships between input and output, during the training stage, and obtained Average Accuracy percentage (AA) of 90.00% and the coefficient of correlation (R) was 96%

REFERENCES

[1] Alavala, R.C. (2008). "*Fuzzy Logic and Neural Networks: Basic Concepts and Applications*". Retrieved December 22, 2010.

[2] Al-Zwainy, Faiq, M. S. (2009), "*The Use of Artificial Neural Network for Estimating Total Cost of Highway Construction Projects*", a thesis submitted to the Civil Engineering Department, College of Engineering, Baghdad University, Ph.D.

[3] Demuth, H., Beale, M., and Hagan, M. (2006)." *Neural network toolbox User's guide"*, Version 5, Natick, Massachusetts.

[4] Gwang-Hee K, Sang-Hoon A, Kyung-In K. (2004) "*Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning*". Journal Building and Environment. Vol. 39, pp 1235-1242.

[5] Haykin, S. (1999). "*Neural Networks: A Comprehensive Foundation*", Upper Saddle River, NJ: Prentice Hall International Inc.

[6] Jain, A. K., Mao, J., and Mohiuddin, K. M. (1996). "*Artificial neural networks: A tutorial*." *Computer*, 29(3), 31-44.

[7] Karna, K. N., and Breen, D. M. (1989). "*An artificial neural networks tutorial: Part 1– basics*." *The international journal of neural networks*, 1(1), 4-23.

[8] Rumelhart, D. E., McClelland, J. L and the PDP research group (1986).” *Parallel Distribution Processing: Exploration in the microstructure of cognition”, Volume 1: Foundations*, The MIT Press, Massachusetts.

[9] I-Cheng Yeh, (1998)“ Modeling of strength of high performance concrete using artificial neural networks,” Cement and Concrete Research, Vol. 28, №12, pp. 1797–1808

[10] Ahsanul Kabir, Md Monjurul Hasan, Khasro Miah, (2013) “ Strength Prediction Model for Concrete”, ACEE Int. J. on Civil and Environmental Engineering, Vol. 2, №1.

[11] Jaber, F.K., Jasim, N.A. & Al-Zwainy, F.M. (2020). Forecasting techniques in construction industry: earned value indicators and performance models. *Scientific Review Engineering and Environmental Sciences, 29 (2)*, 234-243. doi: 10.22630/PNIKS.2020.29.2.20

[12] Ibraheem A. A., Duaa A., Faiq M. S. Al-Zwainy (2020). Predicting Earned Value Indexes in Residential Complexes’ Construction Projects Using Artificial Neural Network Model. *International Journal of Intelligent Engineering and Systems, 13 (4)*, 248-259.

[13] Benu Singh, Sunita Bansal and Puneet Mishra, (2016) Artificial Neural Network Modeling and Optimization In Honing Process, *International Journal of Computer Engineering and Technology*, 7(3), pp. 67–77.

[14] Chiranjit Dutta and Dr. Niraj Singhal, (2019) A Hybridization of Artificial Neural Network and Support Vector Machine for Prevention of Road Accidents in Vanet, *International Journal of Computer Engineering and Technology*, 10 (1), pp. 110-116

[15] Ruby Singh and Dr. Niraj Singhal, (2019) An Optimized Vehicle Parking Mechanism Using Artificial Neural Network, *International Journal of Computer Engineering and Technology*, 10 (1), pp. 102-109