CHAPTER FIVE

DEVELOPING OF THE ANN MODEL

5.1 Introduction

In this chapter one ANN Model is developed for predicting compressive strength of High Strength Concrete following the procedure described previously in chapter 4 and using all information reviewed in chapter 2 and 3. The chapter includes the procedure of the developed ANN model.

The Optimization Modeling System "Solver" in the Microsoft Office Excel (2010) was used to build the current ANN model with three layers feed-forward and back propagation training system. Actual and reliable data as many as possible were carefully collected from previous studies. They were studied and divided into two sets; training set and testing set. The training set of the database was used to train the model. The performance of the model was monitoring during training process and the network error was analyzed as well. Testing set of the database was utilized for the evaluation and final acceptance of the developed ANN model. A parametrical analysis based on the developed ANN model was discussed to determine the influence and role of the parameter affecting compressive strength of High Strength Concrete.

5.2 Network Architecture with Back-Propagation

An ANN is a collection of simple processing units or nodes connected through links called connections. The topology or architecture of neural networks may be presented schematically, as in Figure (5.1). In this figure, a three-layered feed-forward ANN is represented in the form of a directed graph, where the nodes represent the processing unit, the arcs represent the connections, and the arrowheads on the arcs indicate the normal direction of signal flow.

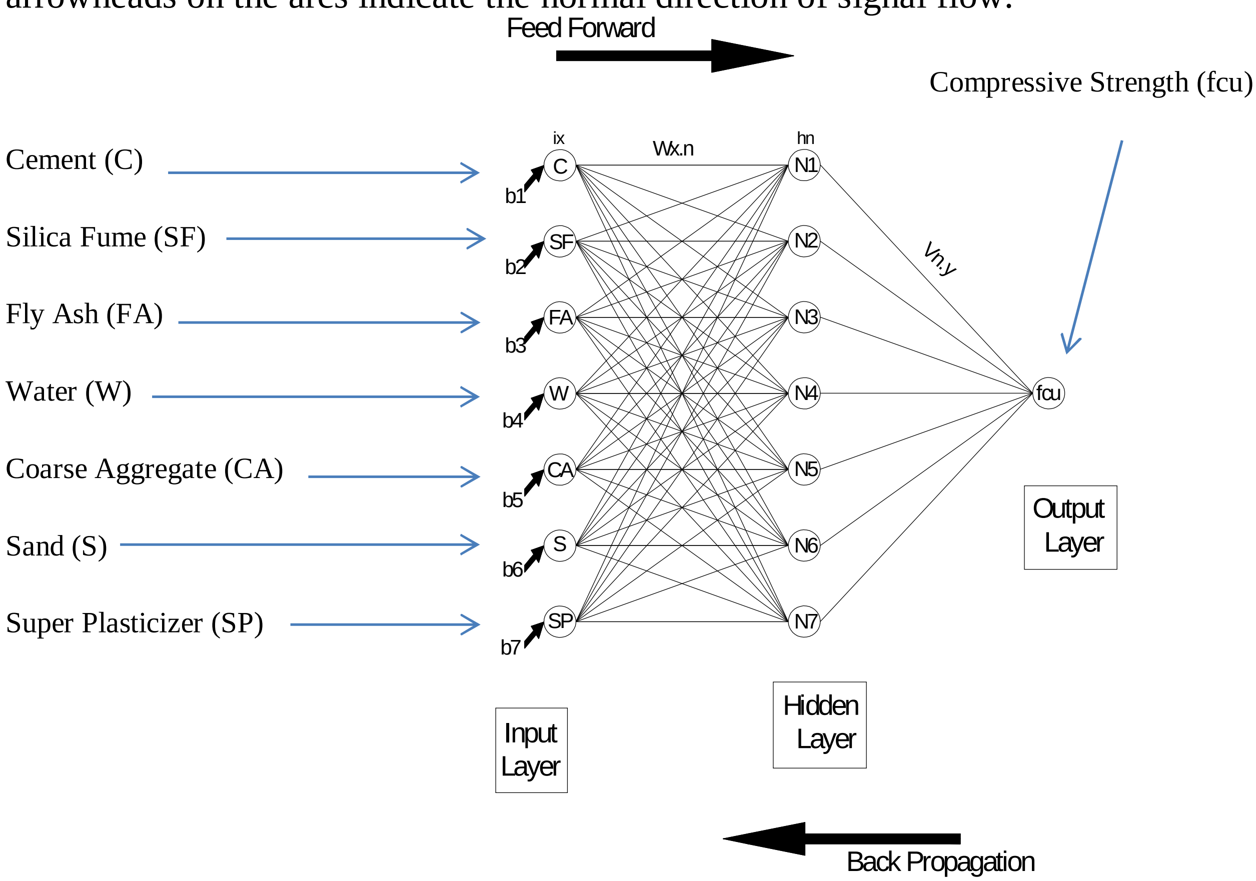

Figure (5.1): Three Layers Feed-Forward ANN Model of Back Propagation for Compressive Strength of High Strength Concrete. “Seven Inputs, One Hidden Layer with Seven Neurons and One Output”.

The processing units may be grouped into layers of input, hidden and output processing units. Also where W & V indicates the weighs matrices and b1-7 indicate the bias vector. Among the available techniques to train a network, back-propagation is generally known to be the most powerful and widely used for NN applications, especially in civil engineering applications (Mansour et al., 2004). To get some desired outputs, weights, which represent connection strength between neurons and biases, are adjusted using a number of training inputs and the corresponding target values. The network error, difference between calculated and expected target patterns in a multi-layered feed-forward network, is then back propagated from the output layer to the input layer to update the network weights and biases. The adjusting process of neuron weights and biases are carried out until the network error arrives at a specific level of accuracy, see (appendix A).

5.3 Data Collection

The development of neural network models needs as many reliable training data as possible. The training data consist of those input parameters affecting the system and the corresponding output parameters. These input data can be experiment test data, reliable empirical data or theoretical results. The current research utilized experimental test results obtained from previous studies. All previous experiments used in this study have identical test setup. Strength of concrete is tested after 28 days (cube test).

The data were carefully collected from previous studies and references, these are: (Amudhavalli and Mathew, 2012), (Muthupriya, et al, 2011), (Yaqub and Bukhari, 2006), (Gupta, 2013), (Scholar, 2015), (Chopra et al, 2015), (Annadurai and

Ravichandran, 2014), (Rashid and Mansur, 2008), (SHETTY, 2008), (Concrete, Microstructure, Properties, and Materials).

For building this model, training and testing use the available experimental results for 193 specimens produced with 7 different mixture proportions are used. The data used in the multi-layer feed forward neural networks models are designed in a format of seven input parameters are, cement(C), silica fume (SF), fly ash (FA), water (W), coarse aggregate (CA), sand (S), and super plasticizer (SP). Accordingly to these input parameters, in the multi-layer feed forward neural networks models are used to predict the compressive strength (f_{cu}) of HSC concrete.

The experimental results for training data are shown in (appendix B). Table (5.1) shows tiny information from the results for demonstration.

The data were grouped randomly into two subsets, i.e., a training set of 164 data (see appendix B) and a testing or validation set of 29 data as shown in table (5.4).

The flow chart below shows the developing process for a neural network forecasting model.

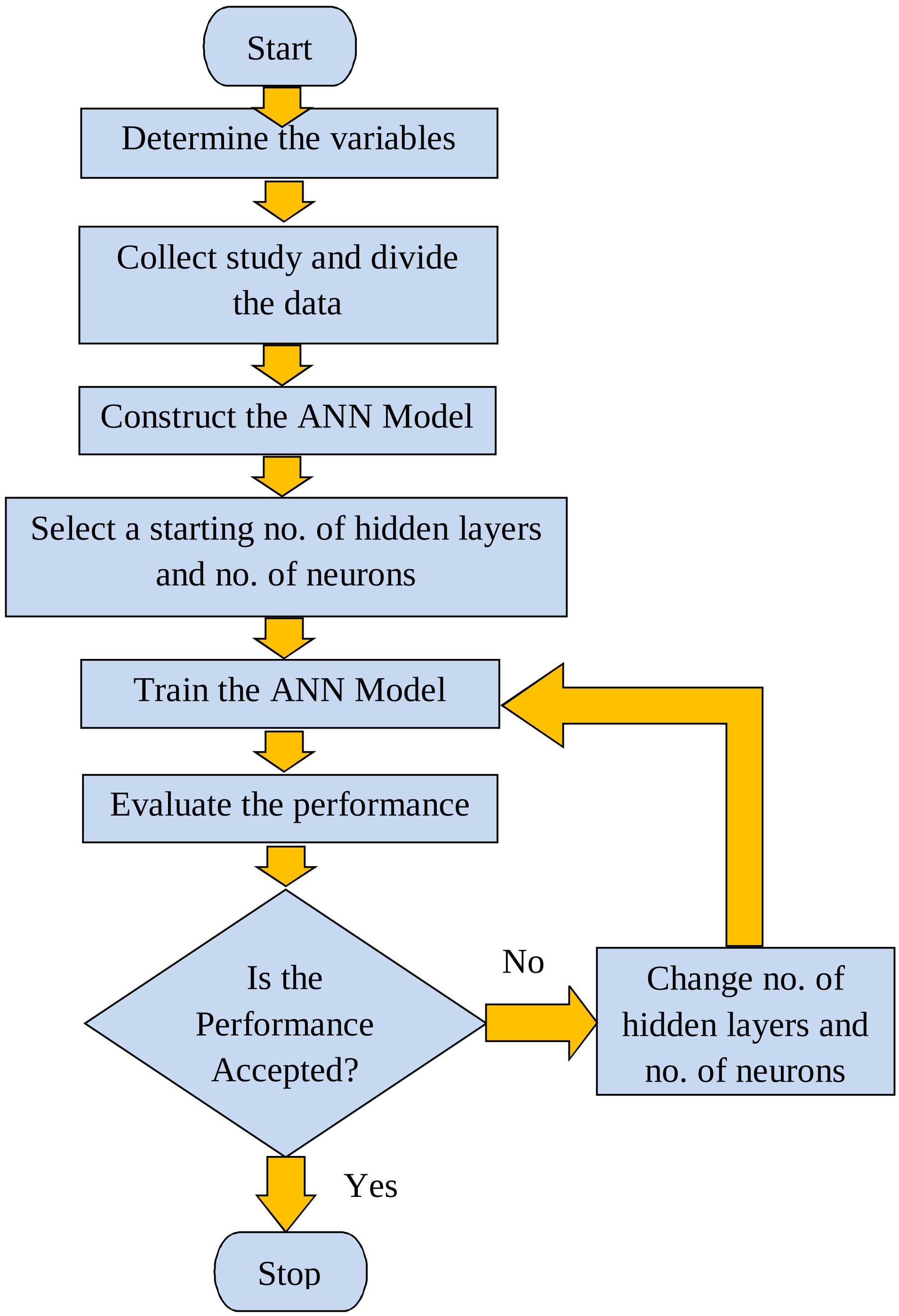

Table (5.1): Training Data Sample for Demonstration.

S/N	Main Components + Additives							Compressive Strength MPa		Error	
	Cement Kg/m³	Silica Fume Kg/m³	Fly aAsh Kg/m³	Water Kg/m³	Coares Aggregate Kg/m3	Sand Kg/m³	Super Plasticizer Liter/m³	Experimental Results	Predicted Results	Square Error	Relative Error %
1	529.01	42.87	0.00	169.28	1171.80	594.58	9.23	67.00	60.77	38.83	(9.30)
2	514.72	57.16	0.00	169.86	1171.80	589.35	9.75	65.20	59.83	28.81	(8.23)
3	486.12	28.58	57.16	170.14	1171.80	577.28	16.72	66.00	60.41	31.20	(8.46)
4	457.53	57.16	57.16	169.29	1171.80	566.82	17.19	64.80	61.96	8.07	(4.38)
5	450.00	0.00	0.00	220.50	1228.50	616.50	0.00	46.60	44.14	6.04	(5.27)
6	475.00	0.00	0.00	199.50	1040.25	498.75	0.00	54.50	52.49	4.05	(3.69)
7	425.00	0.00	0.00	221.00	858.50	607.75	0.00	40.00	40.79	0.63	1.98
8	450.00	0.00	0.00	220.50	837.00	580.50	0.00	45.30	45.57	0.07	0.59
9	450.00	0.00	0.00	229.50	891.00	175.50	0.00	42.70	43.01	0.10	0.72
10	475.00	0.00	0.00	218.50	817.00	560.50	0.00	48.70	49.68	0.97	2.02
11	475.00	0.00	0.00	228.00	869.25	598.50	0.00	45.50	44.67	0.68	(1.81)
12	400.00	0.00	0.00	180.00	1080.00	440.00	0.00	47.90	50.13	4.98	4.66
13	425.00	0.00	0.00	191.25	1139.00	463.25	0.00	50.40	49.71	0.48	(1.38)
14	450.00	0.00	0.00	189.00	1102.50	441.00	0.00	54.10	54.57	0.22	0.87
15	400.00	0.00	0.00	200.00	884.00	528.00	0.00	44.00	43.12	0.77	(2.00)
16	425.00	0.00	0.00	199.75	862.75	505.75	0.00	47.40	46.82	0.33	(1.22)
17	425.00	0.00	0.00	208.25	926.50	548.25	0.00	44.70	44.83	0.02	0.30
18	450.00	0.00	0.00	198.00	837.00	481.50	0.00	50.90	50.62	0.08	(0.55)
19	450.00	0.00	0.00	211.50	900.00	526.50	0.00	48.10	48.94	0.71	1.75
20	475.00	0.00	0.00	199.50	798.00	451.25	0.00	54.10	54.05	0.00	(0.09)
21	475.00	0.00	0.00	209.00	874.00	503.50	0.00	51.30	53.11	3.28	3.53
22	411.00	102.20	0.00	143.85	1044.00	773.00	5.11	67.33	67.02	0.10	(0.46)
23	386.00	127.75	0.00	142.82	1044.00	773.00	5.11	63.11	63.99	0.78	1.40
24	396.60	16.50	0.00	154.67	722.00	826.00	7.00	75.20	74.74	0.21	(0.61)
25	380.00	33.00	0.00	144.40	722.00	826.00	7.00	86.10	82.85	10.56	(3.77)

5.4 Construction of ANN Model Using Microsoft Office Excel

The Optimization Modeling System "Solver" in the Microsoft Office Excel (2010) was used to build the current neural network model.

Training strategy of the ANN model: It was decided to use a feed forward back propagation to develop the neural networks.

The test set is used as a further check for the generalization of the ANN; nevertheless it has an independent process that doesn't affect the training procedure.

5.5 Data Scaling

Data scaling is an essential step for network training. Upper and lower limits of output from a sigmoid transfer function are generally 1 and 0, respectively. Scaling of the inputs to the range [0, 1] greatly improves the learning speed, as these values fall in the region of the sigmoid transfer function where the output is most sensitive to variations of the input value. Therefore it is recommended to normalize the input and output data before presenting them to the network. Scaling data can be linear or non-linear, depending on the distribution of the data. Most common functions are linear and logarithmic functions (Othman, 2011). A simple linear normalization function within the values of zero to one is:

$$S = \frac{P - P_{min}}{P_{max} - P_{min}} \qquad \text{Eq. (5.1)}$$

Where, S is the normalized value of the variable P, P_{min} and P_{max} are the variable minimum and maximum values, respectively.

5.6 Model Building

The mode of operation of the three-layer feed forward network is described by;

$$h_n = \phi(V_n) = \phi\left(\sum_{x=0}^{M} W_{n,x}\, i_x\right) = \phi\left(\sum_{x=1}^{M} W_{n,x}\, i_x + b_n\right) \qquad \text{Eq. (5.2)}$$

$$\sigma_y = \phi(V_y) = \phi\left(\sum_{n=0}^{N} V_{y,n}\, h_n\right) = \phi\left(\sum_{n=1}^{N} V_{y,n}\, h_n + b_y\right) \qquad \text{Eq. (5.3)}$$

where i_x is the scaled input value transmitted from the x^{th} input neuron; h_n, activity level generated at the n^{th} hidden neuron; σ_y, activity level generated at the y^{th} output neuron; $w_{n,x}$ and $v_{y,n}$, weights on the connections to the hidden and output layers of neurons, respectively; b_n and b_y , weighted biases and φ(V), activation function, in this case, the sigmoid function:

$$\phi(V) = \frac{1}{[1+\exp(-\lambda V)]} \qquad \text{Eq. (5.4)}$$

λ being sigmoidal gain.

Equations (5.2) and (5.3) if expanded in terms of scaled parameters will appear in the similar equation form as presented by (Rajasekarans and Nalinaa, 1997). For instance, considering sigmoidal gain to be unity, the output of the first neuron of hidden layer, $v_{y,1}$ may be expressed in terms of normalized input parameters as:

$$V_{y,1} = \frac{1}{1+e^{-h}} \qquad \text{Eq. (5.5)}$$

Where h_1 is given as;

$$h_1 = w_{11}\, x_{\text{norm},\,1} + w_{21}\, x_{\text{norm},\,2} + \ldots\ldots + w_{71}\, x_{\text{norm},\,7} + b_1 \qquad \text{Eq. (5.6)}$$

In which w_{11}, w_{21}, w_{31},……… , w_{71} are the connecting weights between the first hidden neuron to normalized input data, $x_{\text{norm},1}$, $x_{\text{norm},2}$, $x_{\text{norm},3}$,…., $x_{\text{norm},7}$ corresponding to the compressive strength parameters and b_1 is the bias.

The Microsoft Office Excel Solver tool "Generalized Reduced Gradient (GRG) nonlinear optimization code" was used for reducing the errors by changing the adjustable cells, (see appendix c).

5.7 Network Error Analysis

The evaluation and validation of an ANN prediction model can be done by using common error metrics such as the mean squared error (MSE).

The mean squared error term (MSE) penalizes distant errors, i.e. clear misses, more severely and therefore favors a network with few or no distant errors. This means that the network may have many uncertain predictions which has a lower MSE, on the other hand, takes large errors into account, but does not weigh them more heavily. This means that the network may have many predictions with very small errors but it may have a few clear misses with very large error.

A measure of linearity is the Pearson product moment correlation coefficient, R given as Eq. (5.7) The R value reflects the extent of the linear relationship between two data sets. For example the R value between the set of predicted values of a model and the set of experimental values. A value of R equal to 1.0 means that the predicted values are equal to the experimental values. A perfect linear fit! Hence, a model with value of R very close to one represents a superior model, when the predicted and experimental values are compared.

$$R = \frac{n\left(\sum xy\right)-\left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2-\left(\sum x\right)^2\right]\left[n\sum y^2-\left(\sum y\right)^2\right]}} \qquad \text{Eq. (5.7)}$$

Where n = number of data for the two data sets, x and y.

5.8 Statistics of Experimental Tests:

Table (5.2) shows the statistical parameters of the training set data while Table (5.3) shows the statistical parameters of the testing set data.

Table (5.2): Statistics of Experimental Data "Training set".

	Cement kg/m^3	Silica Fume kg/m^3	Fly Ash Kg/m^3	Water Kg/m^3	Course Aggregate Kg/m^3	Sand Kg/m^3	Super Plasticizer Liter/m^3	Experimental fcu. (MPa)
No. of data	164	164	164	164	164	164	164	164
Min. Value	232.00	0.00	0.00	122.00	678.00	175.50	0.00	40.00
Max. Value	637.00	165.00	187.00	229.50	1419.00	896.00	31.00	127.00
Range	405.00	165.00	187.00	107.50	741.00	720.50	31.00	87.00
Mean	453.87	25.62	26.19	174.19	1062.00	628.13	5.52	62.44
Std. Dev.	70.96	38.00	42.80	25.53	127.47	133.50	6.86	16.20
Median	450.00	0.00	0.00	171.36	1049.00	617.75	2.20	62.00

Table (5.3): Statistics of Experimental Data "Testing set".

	Cement Kg/m^3	Silica Fume Kg/m^3	Fly Ash Kg/m^3	Water Kg/m^3	Course Aggregate Kg/m^3	Sand Kg/m^3	Super plasticizer $Liter/m^3$	Experimental fcu.(MPa) Kg/m^3
No. of data	29	29	29	29	29	29	29	29
Min. Value	297.00	0.00	0.00	122.00	899.00	375.00	0.00	42.50
Max.Value	550.00	106.00	121.00	209.00	1235.00	817.00	19.00	111.00
Range	253.00	106.00	121.00	87.00	336.00	442.00	19.00	68.50
Mean	462.46	33.29	24.03	167.42	1073.12	644.82	7.8	66.14
Std. Dev.	69.14	32.94	37.01	24.63	75.46	127.93	7.81	18.26
Median	475.00	30.00	0.00	171.72	1044.00	630.00	5.00	65.77