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# DESIGN OF SELF COMPACTING CONCRETE USING ARTIFICIAL NEURAL NETWORKS

# تصميم الخرسانة ذاتية الدمك باستخدام الشبكات العصبية

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## ملخص:

أصبحت الخرسانة ذاتية الدمك تمثل ثورة في عالم الخرسانة لما تتميز به من فوائد عدة. واتجه العالم اليوم الى اساليب حديثة لتصميم الخلطات الخرسانية وخصوصا الخرسانة ذاتية الدمك بما تحتويه من اضافات متعددة فتمثل متغيرات عديدة بالخلطة الخرسانية، وفى سياق ذلك اصبحت الطرق التقليدية غير دقيقة.

وفى اطار انتشار البرامج الحديثة مثل الشبكات العصبية، أمكن في هذا البحث تطويع هذا البرنامج لاستقبال خواص الخلطات ذاتية الدمك متمثلة في اجهاد الضغط و الانسياب الحر لاخراج مكونات الخلطة المستهدفة بعد تغذية البرنامج بعدد كبير من الخلطات المعملية حيث امكن تجميع ٢٢٥ خلطة ذاتية دمك من خلال ٣٤ بحثا بنسب وخواص مختلفة وقسمت الى قسمين:

- القسم الاول عباره عن ثلثى العينات الكلية وتمثل ١٥٠ خلطة لتعريف البرنامج وتدريبه عليها حيث تم ادخال خواص الخرسانة كمدخلات وادخال مكونات الخلطات كمخرجات وبعد محاولات عديدة وصلت الى ١٧٦ محاولة تم التوصل الى افضل شكل للنموذج وهو استخدام طبقتين مختفيتين من العقد هى ١٤ للطبقة الأولى و١٠ للطبقة الثانية واصبح تركيب النموذج ( ٢-١٤-١٠-٧ ) حيث عدد المتغيرات الداخلة ٢ ويمثلها اجهاد الضغط والانسياب الحر وعدد المتغيرات الخارجة (المستهدفة) ٧ ويمثلها المستهدف وهو كمية الاسمنت-المواد الناعمة-الركام الصغير-الركام الكبير- السوبربلاستيسيزر-الاضافات المدعمة للزوجة-نسبة الماء الى المواد الاسمنتية.
- القسم الثانى عبارة عن ثلث العينات وتمثل ٧٥ خلطة لاختبار البرنامج بعد تعريفه بخلطات لم يعرفها مسبقا لتحديد قيمة الاداء للبرنامج.

أعطت نتائج الاختبار اخطاء مقبولة فيما عدا نتائج المكونات التى يبدأ مجالها من الصفر مثل المواد الناعمة و المواد المدعمة للزوجة حيث اعطت بعضها بعض القيم السالبة نظرا لما يضاف اليها من اخطاء سالبة لذا نوصى بعمل نموذج به ٦ مدخلات فقط اذا كان المستهدف من تصميم الخلطة عدم وجود بعض المكونات مثل المواد المدعمة للزوجة على سبيل المثال وذلك لضبط المخرجات وجعلها اكثر دقة ولتجنب القيم السالبة لها.

ولكى يتم التاكد عمليا من مخرجات البرنامج تم اعداد ٢٠ خلطة ذاتية الدمك نسبها وخواصها غير موجودة بالمتغيرات التى عرف بها البرنامج وقد تم التوصل الى تصميم الخلطات ذاتية الدمك للعشرين خلطة عن طريق ادخال خواص الخرسانة وهى اجهاد الضغط والانسياب الحر للحصول على نتائج البرنامج ومقارنتها بنسب الخلط المعملية وتم التوصل الى قيم متقاربة عن المستهدفة ومتباعده في بعض الاحيان لارتباط القيم الداخلة للبرنامج باكثر من خلطة من القيم

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المعرف بها البرنامج فتعطى تصميم خلطة بنسب يمكن الاعتماد عليها حيث يقل او يزيد نسب تصميم الخلطة عن المستهدف بنسب معقولة بما يحقق نفس خواص الخلطات المختبرة.


# ABSTRACT:

***Application of artificial neural networks (ANNs) model to design the mix component of self compacting concrete (SCC) with desirable properties, compressive strength and slump flow, is described in this research Artificial Neural Networks (ANNs) have recently been introduced as an efficient artificial intelligence modeling technique for applications involving a large number of variables, especially with highly nonlinear and complex interactions among input/output variables in a system without any prior knowledge about the nature of these interactions. Various types of ANN models are developed and used for different problems. In this paper, an artificial neural network of the feed-forward back-propagation type has been applied for the prediction of self compacting concrete mixtures. The main targets are SCC components and the inputs interred are compressive strength and slump flow. Due to the complex non-linear effect of compressive strength and slump flow properties on the SCC components, the ANN model is used to predict the components of SCC parameters (mix components). SCC component parameters were outputted according to a multi mixes taken from 34 researches [1-34] related with self compacting concrete which contains the compressive strength and slump flow test results. Mix component values are considered as the aim of the prediction. A total of 225 specimens were selected from the laboratory results of about 34 researches. The system was trained and validated using 150 training mixes chosen randomly from the data set and tested using the remaining 75 mixes. About 20 mixes of experimental SCC not found in the entered data were performed experimental in order to simulate the program and compare between experimental and predicted mix design.***

***Results indicate that SCC components can be predicted with reliable values to the experimental results using the ANN method.***



*Keywords:*

**Self compacting concrete; Compressive strength; Slump flow; Neural Network.**


# 1-INTRODUCTION

Concrete has been used as a construction material for more than a century. During this period of time, concrete has undergone a continuous development, e.g. the growing use of secondary cementitious materials in the binding phase. The use of binder admixtures in the production of concrete with enhanced performance (also known as High Performance Concrete or simply HPC) has received a great amount of attention recently [35].

One of the most important binder admixtures to offer a significant contribution to HPC production is silica fume, a pozzolanic material [36,37].

Concrete, as a non-homogeneous material, consists of separate phases; hydrated cement paste, transition zone and aggregate. Although most of the characteristics of concrete are associated with the average characteristics of a component microstructure, the compressive strength and failure of concrete are related to the weakest part of the microstructure. Cement paste properties are of great significance in concrete technology. The compressive strength of cement paste is mainly related to Van der Walls forces. Therefore, the more compacted the concrete, the higher is the compressive strength. One porosity reducing factor is the water-cement ratio and the other factor that affects concrete porosity is filler materials, such as silica fume [36,37].

In recent years, ANNs have shown exceptional performance as regression tools, especially when used for pattern recognition and function estimation. They can capture highly non-linear and complex relations among input/output variables in a system without any prior knowledge about the nature of these interactions.

Unlike traditional parametric models, these models are able to construct a supposedly complex relationship between input and output variables with an excellent level of accuracy compared with that of conventional methods [38]. The main advantage of ANNs is that one does not have to assume an explicit model form, which is a prerequisite in the parametric approaches. Indeed, in ANN models, a relationship of a possibly complicated nature between input and output variables is generated by the data points. In comparison to parametric methods, ANNs can deal with relatively imprecise or incomplete data and approximate results, and are less vulnerable to outliers. They are highly parallel, that is, their numerous independent operations can be executed simultaneously [39]. Basma et al. [40] proposed a method for the prediction of cement degree of hydration using ANN.

The results indicated that the ANNs are very efficient in predicting the concrete degree of hydration with great accuracy using minimal processing data. Nehdi et al. [41] applied a neural network model for performed foam cellular concrete. Results showed that the production yield, foamed density, unfoamed density and the compressive strength of cellular concrete mixtures can be predicted much more accurately using the ANN method compared to existing parametric methods. Marianne, T.J. [42] designed a neural network to investigate the influence of different parameters on the salt frost resistance of concrete. Ju-Won Oh et al. [43] developed an ANN model for the proportioning of concrete mixtures. Nehdi et al. [44] used an ANN model for predicting the performance of self-compacting concrete mixtures. Zong, Gung and Yun [45] utilized an automatic knowledge acquisition system, based on neural networks, to design concrete mixtures. In a later work, Gung and Zong [46] proposed a method to predict 28-day compressive strength by using multi layer feed forward neural networks. Lai and Serra [47] developed a model, based on neuro computing, for prediction of the compressive strength of cement conglomerates.

Yeh [48] developed a strength based Artificial Neural Network (ANN) model, which was found to be more accurate than the one based on regression analysis.

It was also discovered that his ANN model gave the detailed effects of the proportions of each variable from the concrete mixtures. Dias and Pooliyadda [49] used back propagation neural network models to predict the strength and slump of ready mixed ordinary concrete and high strength concrete, in which chemical admixtures were used. Attempts have been made in the past to devise a kinetic model for cement paste properties to predict the phenomena occurring in concrete, but the focus of these models has been on predicting density, compressive strength, deformation under loading, the cracking of sufficiently hardened concrete and etc. The models have not yet reached the stage where they can explain the changes in the physical properties of the cement paste portion of the concrete [39-49]. Predicting the properties of cement paste is of great significance and difficult to achieve as a function of the mixture gradient and physical properties of concrete, hence, a nonlinear prediction model needs to be considered. The uncertainties associated with the parameters affecting the SCC mixture of cement paste make it difficult to exactly estimate such properties [36,39]. Knowing the properties of cement paste, a better understanding of concrete performance properties can be taken into account [36,37].

Considering the influence of silica fume on the transition zone and cement paste and the complex and nonlinear effect of silica fume on concrete cement paste, a set of experiments were carried out on cement paste with different water-cementitious materials and silica fume unit contents, in order to investigate the effect of silica fume on cement paste. An ANN model is then developed, based on the data produced, to predict SCC mixture parameters.

## 2-NEURAL NETWORKS

ANN modeling, a paradigm for computation and knowledge representation is originally inspired by the understanding and abstraction of the biological structure of neurons and the internal operation of the human brain. A neural network is a network of many simple processors that are called nodes. A multilayer perceptron may be thought of as consisting of layers of parallel data processing cells. Each node (neuron) has a small amount of local memory. Nodes in the input layer only act as buffers for distributing the input signals to nodes in the hidden layer. The nodes are connected by connections; each usually carrying numeric data called weights, encoded by any of the existing methods. Each node in the hidden layer sums up its input signals after weighting them with the strengths of the respective connections from the input layer and computes its output as a function of the sum. The nodes operate only on the local data and on the inputs they receive via the connections. The differences between the computed output and the target are combined together by an error function to give the network the verification set, and used to keep an independent check of the progress of the algorithm. Training of the neural network is stopped when the error for the verification set begins to increase [38,39,43].

The main principle of neural computing is the decomposition of the input-output relationship into a series of linearly separable steps using hidden layers [39].

There are three distinct steps in developing an ANN based solution:

1. Data transformation or scaling;

2. Network architecture definition, where the number of hidden layers, the number of nodes in each layer and the connectivity between the nodes are set;

3. Construction of a learning algorithm in order to train the network [38,41].

Fig. (1) Shows the simple architecture of a typical network that consists of an input layer, hidden layers, an output layer and connections between them.

Nodes in the input layer represent possible influential factors that affect the network outputs and have no computation activities, while the output layer contains one or more nodes that produce the network output.

Hidden layers may contain a large number of hidden processing nodes. A feed-forward back-propagation network propagates the information from the input layer to the output layer, compares the network outputs with known targets and propagates the error from the output layer back to the input layer, using a learning mechanism to adjust the weights and biases [38,43].

In general, the net input to each node is calculated as:

$$N_j^l = \sum_{i=1}^{n} W_{ji}^l . X_i^{l-1} + \beta_j^l,$$

Where $W^l_{ji}$ is the weight that connects node j in layer l to node i in layer l - 1; n is the number of nodes in layer l -1; $\beta^l_j$ is a threshold value assigned to node j in layer l; and $X^{l-1}_i$ is the input coming from node i in layer l -1 to node j in layer l. The net input, $N^l_j$, is then modified by an activation function, f, to generate an output value, $Y^l_j$, given by:

$$Y_j^l = f(N_j^l),$$

Where f is a nonlinear activation function assigned to each node in the network. The learning mechanism of this back-propagation network is a generalized delta rule that performs a gradient-descent on the error space, in order to minimize the total error between the calculated and desired values at the output layer during modification of the connection weights. The implementation of this algorithm updates the network weights and biases in the direction in which the error decreases most rapidly. Training is accomplished in an iterative manner. Each iteration cycle involves the feed-forward computation followed by an error-backward propagation to modify the connection weights. Convergence depends on the number of hidden layer nodes, learning rate parameters and the size of the data set required to create the proper results. Furthermore, there is no structured algorithm to obtain the optimal structure and parameters of neural networks; therefore, one should find the optimal network by trial and error. The most interesting property of a network is its ability to generalize new cases. For this purpose, an independent data set is used to test the neural network and check its performance. When verification and test errors are reasonably close together, the network is likely to generalize well [38, 43].

Upon successful completion of the training process, a well-trained neural network is not only capable of computing the expected outputs of any input set of data used in the training stage, but should also be able to predict, with an acceptable degree of accuracy, the outcome of any unfamiliar set of input located within the range of the training data [38,41].

# 3-SELECTION OF DATABASE

The selection of the database chosen to train a neural network such that it will be capable of capturing the relationships between the properties of SCC and its mixtures is of great importance. It must be trained on large and comprehensive sets of reliable experimental data that contain influential factors regarding SCC mixtures.

The data set for neural network analysis was a subset from the database of SCC mixes and its corresponding properties. The SCC mixes were measured in the laboratory by chosen several mixes of SCC from 34 references. In this study, cement (C), fine powder (P), fine aggregate (FA), coarse aggregate (CA), superplastisizer (SP), viscosity enhancement agent (VEA) and water-cementitious ratio (W/C) were used for the production of SCC with desired properties, compressive strength and slump flow. Type of cement used was (Type I) of 161 to 680 kg/m$^3$ with the W/C of 0.24 to 0.58 and silica fume unit contents of 0.0 kg/ m3 to 493 kg/ m$^3$ and fine aggregate of 263 to 1270 kg/m$^3$ and coarse aggregate of 370 to 1217 kg/ m$^3$ where VEA was 0 to 5.7 kg/m$^3$ were used to prepare the specimens. All the specimens were cured for 28 days at an average temperature of 20°C. This led to the development of a large number of data sets. Table (1) shows the ranges, average values and standard deviation of all relevant parameters. Ultimately, a total of 225 data pairs have, therefore, been selected from the experimental database, as mentioned above.

# 4-NEURAL NETWORK ARCHITECTURE

There is no effective procedure for identifying the optimal architecture of a network before training. However, it is important for the hidden layers to have a small number of nodes. An excessive number of hidden nodes may cause the network to memorize the training data.

In such cases, the ANN would not be able to interpolate effectively between adjacent training data points. Too few hidden nodes, on the other hand, will limit the network's ability to construct an adequate relationship between input and output variables [38].

The number of hidden layers and nodes are usually determined via a trial and error procedure.

There are some rules to estimate the number of hidden nodes. According to the method suggested by Dave Anderson and George McNeill [38], an upper bound for the number of processing nodes in the hidden layers can be calculated by dividing the number of input-output pairs in the training set by the total number of input and output nodes in the network, multiplied by a scaling factor between five and ten.

Compressive strength and slump flow were represented by the two input nodes, while the output layer contains seven nodes representing cement, fine powder, fine aggregate, coarse aggregate, superplastisizer, VEA and water cement ratio. Following the guidelines suggested by Dave Anderson and George McNeill [38] and some preliminary computations, a network architecture containing two hidden layers was adopted. The first hidden layer included fourteen nodes, while the second hidden layer had ten nodes and a full connection between the nodes in the adjacent layers was selected. The network architecture can be seen schematically in Fig. (2). A free access ANN package ($Q_{net}$) of the feed-forward back-propagation type was used in this study [50].

## 5-TRAINING OF ANN MODEL

The training procedure was carried out by presenting the network with the set of experimental data in a patterned format. Each training pattern includes an input set of two parameters representing the compressive strength and slump flow and a corresponding output set representing SCC mixtures (that is, cement, fine powder, fine aggregate, coarse aggregate, superplastisizer, VEA and water cement ratio). The network is presented with the variables in the input vector of the first training pattern, followed by an appropriate computation through the nodes in the hidden layers and prediction of the appropriate outputs. The error between the predicted output and target value is calculated and stored. The network is then presented with the second training pattern and so on until the network has gone through all the data available for training the network.

The Root-Mean-Square (RMS) of the error is then calculated and back propagated to the network. Biases and weights or the connection strength between nodes are modified during the back propagation phase such that the (RMS) errors are reduced. The process of the introduction of training input-output pairs to the network, calculation of the (RMS) error and, finally, the adjustment of weights and biases to reduce the (RMS) error are referred to as, one iteration. This process continues until convergence is achieved or the maximum number of iterations is reached [38, 41]. The trained ANN model is represented by the connection weights once the above procedure is converged. This process is illustrated in Fig. (3). Trial and error procedure are illustrated in Table (2) where trial of hidden layers were carried out for the Neural Network program in order to obtain optimum number of hidden layers (hl) and performance. Letter (x) represented the trial number of layers. Second column of Table (2) shows the number of trial for each number of layers (x). Best trial was illustrated in the third columns of the table whereas optimum performance illustrated in column 4. After about 176 trials, Results indicated that best trial and performance occurred when using two layers 14 and 10 consequently as hatched in column 4.

To avoid the over-fitting of the neural network model to the data during iterative training, a separate set of the data set was used to validate the model at some intervals during training. Training is stopped when the error for the validation set begins to increase.

The network was trained and validated, based on 150 training patterns chosen randomly from the 225 available data sets. The remaining 75 pairs of independent data were used to test the network after completion of training and validation in order to assess its performance on data to which it has never before been exposed. The training process and the associated ANNs analyses were carried out with an optimal value of learning rate of 0.00338147and maximum number of iterations of 3000 with an error goal of 0.000.

## 6-RESULTS AND DISCUSSION

The network was trained to predict SCC mixtures using a total of 150 training and validating data sets and 75 testing data sets. Figures 4a to 4g compare the output and target values of SCC mixtures for all the 225 available data sets. Figures 5a and 5b show the convergence characteristics of the ANN model during the training and testing phases, respectively.

Fig. (6) Illustrates the distribution of the network outputs versus the target values for the training data sets. All data points are distributed along the optimal agreement line, with the training and testing Root-Mean-Square (RMS) errors of 0.0338147 and 0.0208165, respectively. The correlation between predicted and measured SCC components is seen to be satisfactory. It is generally lower for powder, superplastisizers and VEA values that is because of these parameters includes zero values in some mixes as indicated in Table (2) and figures 4b, 4e and 4f. The relatively larger prediction error and less correlation parameters may, therefore, be associated to high variability in the mixture development rather than the prediction method and may be related to the different types of such materials used in the training set targets. To test the accuracy of the ANN model, the final trained model was called upon to recall the data not used in the training process (150 mixes). A total of 20 mixes, unfamiliar to the network in the range of training data sets, were presented to the ANN model and the network was required to predict the SCC mixture associated with each mixture. The mixture proportion and the measured and predicted values are listed in Table (3).

As mentioned previously, a set of experimental data, including 225 pairs of data, was used in this study, from which 150 training and validating patterns were chosen arbitrarily and the remaining 75 pairs were used as measured data, to test and verify the efficiency and validity of the predicted values by the network. A reliable agreement between the measured and predicted values of SCC is observed, as shown in Fig. (7).

Results of program/experimental mix design ratios of 10 mixes of SCC are illustrated in Fig. (7) Where the mix design prediction was approximately closed to the target mix in some mixes whereas other mixes were relatively closed to targets. The high range of inputs data of compressive strengths and slump flows (SF) makes some properties of compressive strengths and slump flows entered to the program are closed to each others so, outputs may correlate to more than training set data hence, the predicted mix design may result in many training mixes so mix design of outputs may differ from experimental. Tested data were entered to the program by pairs whereas each tested data of compressive strengths and slump flows correlate to the training set as a group which may differ from the pairs of training sets which produce deviation about targets as indicated in Fig. (7). For example tested mix M1 some components increased with related to targets such as powder, aggregates and W/C where as decreasing in cement and superplastisizer were observed. On the other hands tested mix M7 indicated increasing in cement, superplastisizer and W/C whereas decreasing in powder and aggregates was observed. Economical investigation of desired and predicted mixes may be carried out in order to choose the economical mixes as shown in mix M8 which exhibited no powder in the mix design and decreasing in cement and FA where increasing in CA and superplastisize. It can be, therefore, concluded that the proposed ANN model is adequately able to predict SCC components.

Fig. (8) illustrated the average prediction/experimental which indicated that cement, W/C and CA were more closed to the experimental (0.99, 1.02 and 1.03 respectively) where powder, FA and superplastisizer was relatively closed to the experimental (0.9, 1.14 and 0.83 respectively).

## 7-CONCLUSIONS

This paper presents a nontraditional approach to the prediction of the SCC mixture of a cement paste mixture, based on ANN technology.

Based on the findings of this investigation, the following conclusions can be drawn:

1. The proposed model demonstrates the ability of a feed-forward back-propagation neural network to predict the mix component of SCC concrete with reliable accuracy. The model performed quite well in predicting, not only the SCC mixtures used in the training process, but also those of test mixtures that were unfamiliar to the neural network.

2. Predicting the mix proportions of SCC as a function of the SCC mix properties, using analytical and traditional methods, is difficult to achieve as a previous studies, whereas a trained neural network model can predict such mix proportion easily and accurately. Therefore, ANN can provide a drastically powerful alternative approach.

3. Although the prediction capability of any ANN model is limited to data located within the boundaries of the training range, the proposed model can be retrained to include a wider range of input variables by providing additional training sets covering the new range;

4. The existence of powder materials, superplastisizer and VEA in the training model may confuse the model with some negative values of outputs if its ranges stared with zero values.

5. It is recommended to build up a new model for zero values of powder, superplastisizers and VEA if desired in order to adjust the model without any confusion.

6. The average prediction/experimental outputs were more closed to cement, water- cementitious ratios and coarse aggregates (0.99, 1.02 and 1.03) respectively whereas the average prediction/experimental outputs were relatively closed to powder, fine aggregates and superplastisizer (0.9, 1.14 and 0.83) respectively.

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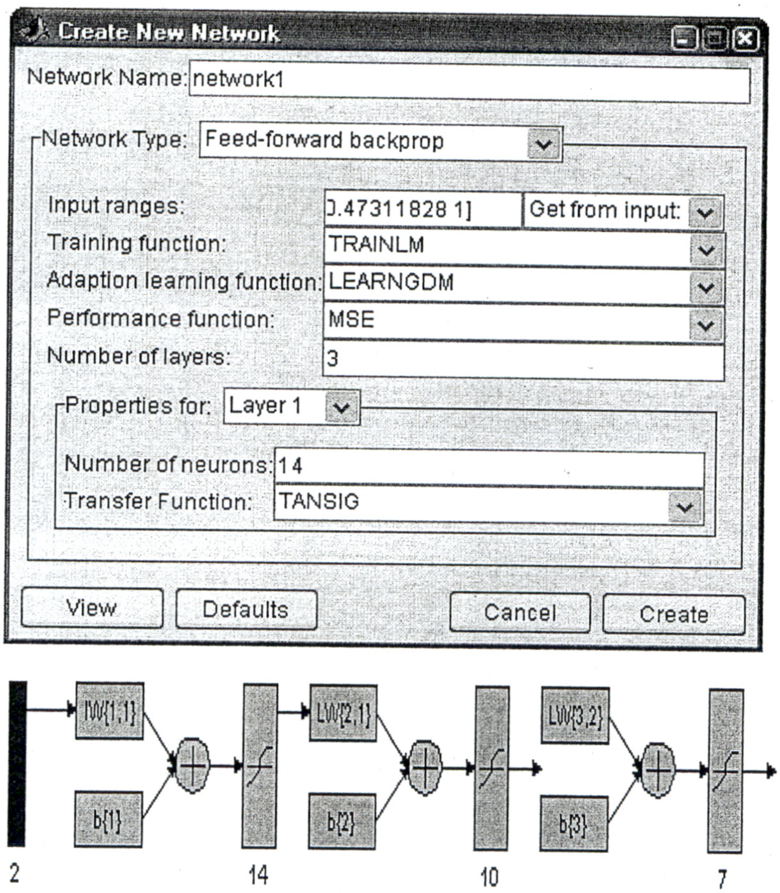


**Fig. (1)Creation of Neural Network and design topology**

**Table (1): Range, average and standard deviation of measured input and output variables.**

| variables | Range | Average | Standard deviation |
|---|---|---|---|
| Y1 ($F_{cu}$) | 200-950 kg/cm$^2$ | 498.1785 | 150.2768 |
| Y2 (Slump flow) | 440-930 mm | 701.36 | 88.13144 |
| X1 (C) | 161-680 kg | 359.5326 | 96.68018 |
| X2 (P) | 0-493 kg | 155.3457 | 75.16052 |
| X3 (FA) | 263-1270 kg | 850.3273 | 118.2341 |
| X4 (CA) | 370-1217 kg | 795.5567 | 104.9805 |
| X5 (SP) | 0.4-30 kg | 7.317022 | 4.601536 |
| X6 (VEA) | 0-5.7 kg | 0.599932 | 1.243141 |
| X7 (W/C) | 0.24-0.58 | 0.36 | 0.047925 |

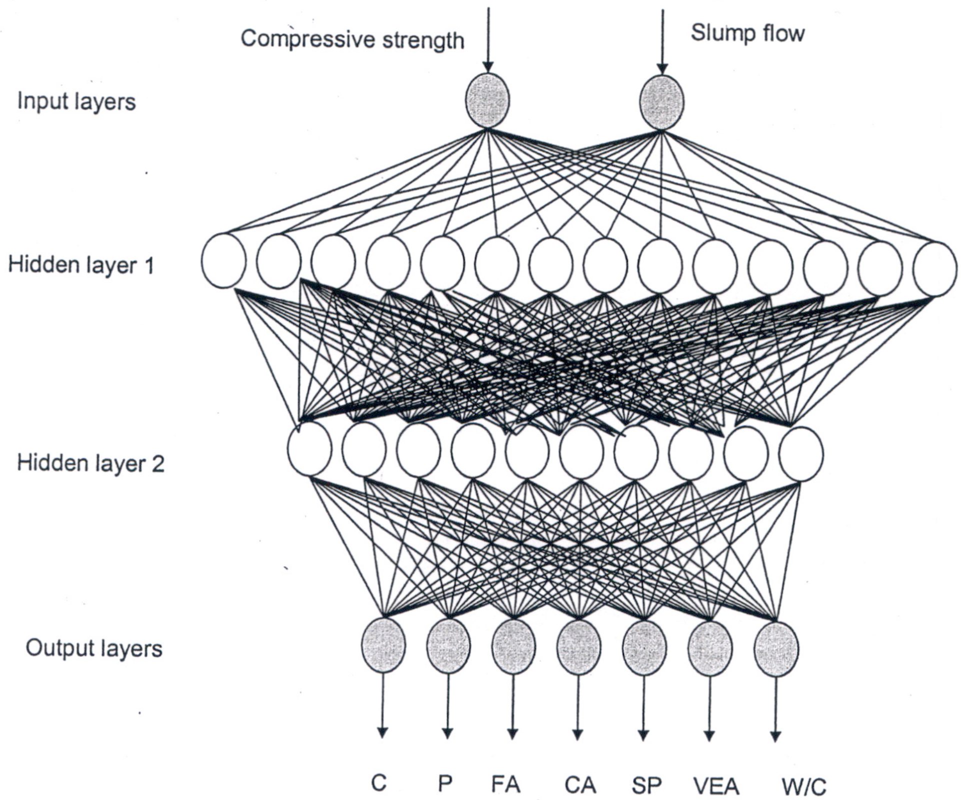


**Fig. (2) Architecture of neural network model**

**Table (2): Trial and error of hidden layers (hl) and performance**

| No. of hl | Number of trial (x) | Best trial | Optimum performance |
|---|---|---|---|
| 2-x-7 | 11 | 2-10-7 | 0.0118565 |
| 2-1-x-7 | 14 | 2-1-11-7 | 0.0143926 |
| 2-2-x-7 | 10 | 2-2-9-7 | 0.0128645 |
| 2-3-x-7 | 13 | 2-3-10-7 | 0.00904575 |
| 2-4-x-7 | 12 | 2-4-10-7 | 0.00880824 |
| 2-5-x-7 | 12 | 2-5-7-7 | 0.00851817 |
| 2-6-x-7 | 13 | 2-6-9-7 | 0.0083789 |
| 2-7-x-7 | 10 | 2-7-8-7 | 0.00655413 |
| 2-8-x-7 | 11 | 2-8-10-7 | 0.006472 |
| 2-9-x-7 | 11 | 2-9-9-7 | 0.00620846 |
| 2-10-x-7 | 10 | 2-10-10-7 | 0.0048537 |
| 2-11-x-7 | 12 | 2-11-8-7 | 0.00540072 |
| 2-12-x-7 | 12 | 2-12-10-7 | 0.00409228 |
| 2-13-x-7 | 13 | 2-13-12-7 | 0.00383568 |
| 2-14-x-7 | 12 | 2-14-10-7 | 0.00338147 |

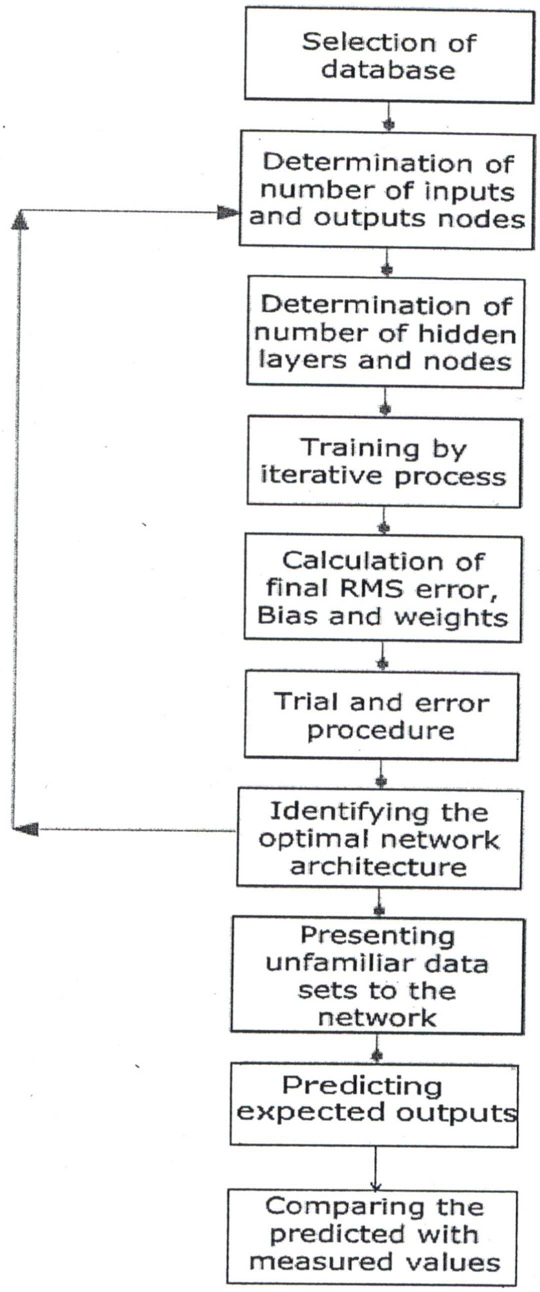


**Fig. (3) Processing neural network model**

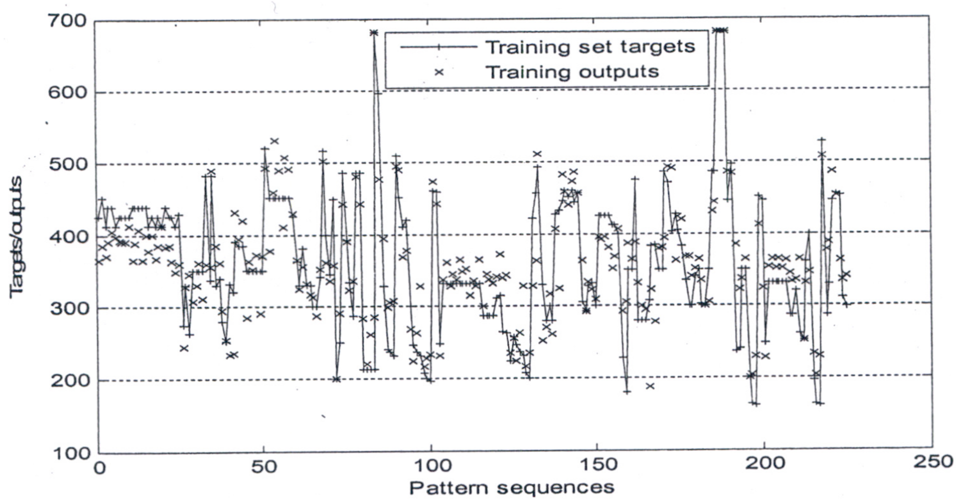


Fig. (4-a) Targets/output vs Pattern sequences (node 1-cement)

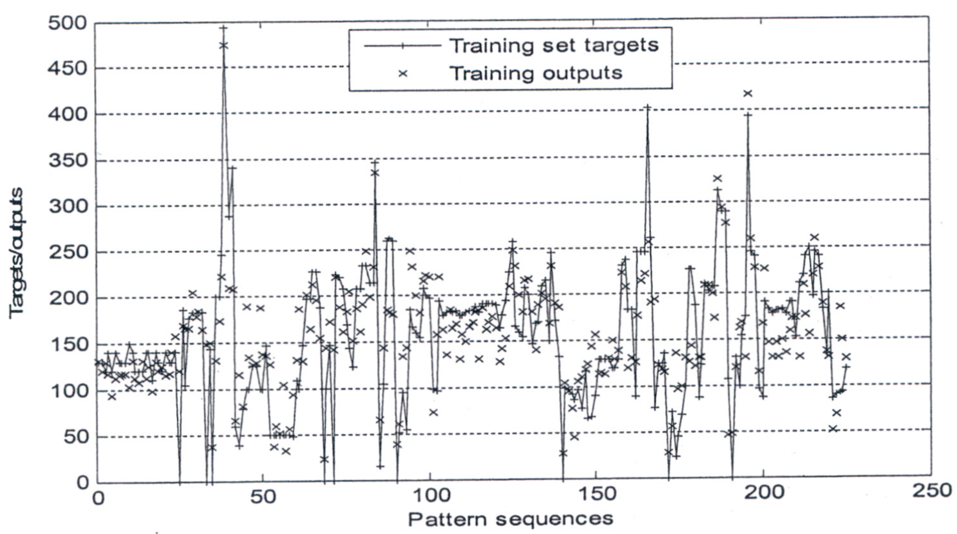


Fig. (4-b) Target/outputs vs Pattern sequences (node 2-powder)

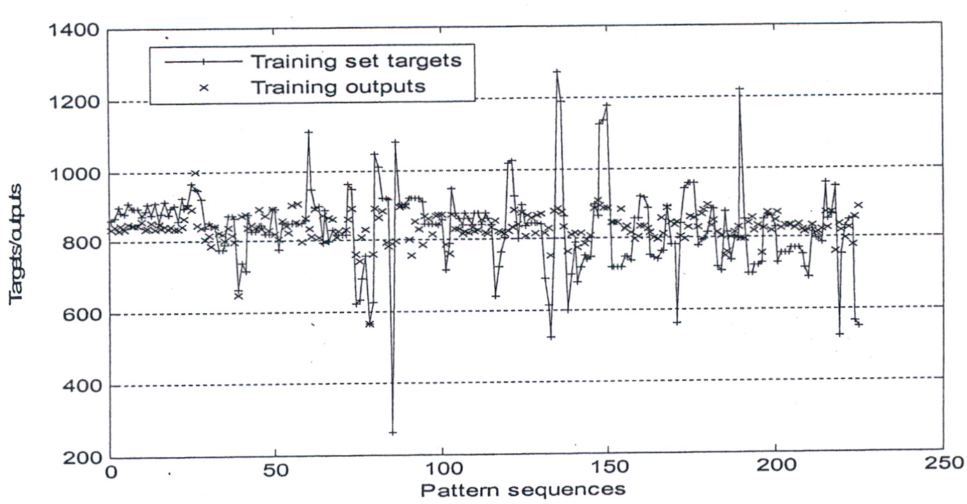


Fig. (4-c) Targets/outputs vs Pattern sequences (node 3-fine agg.)

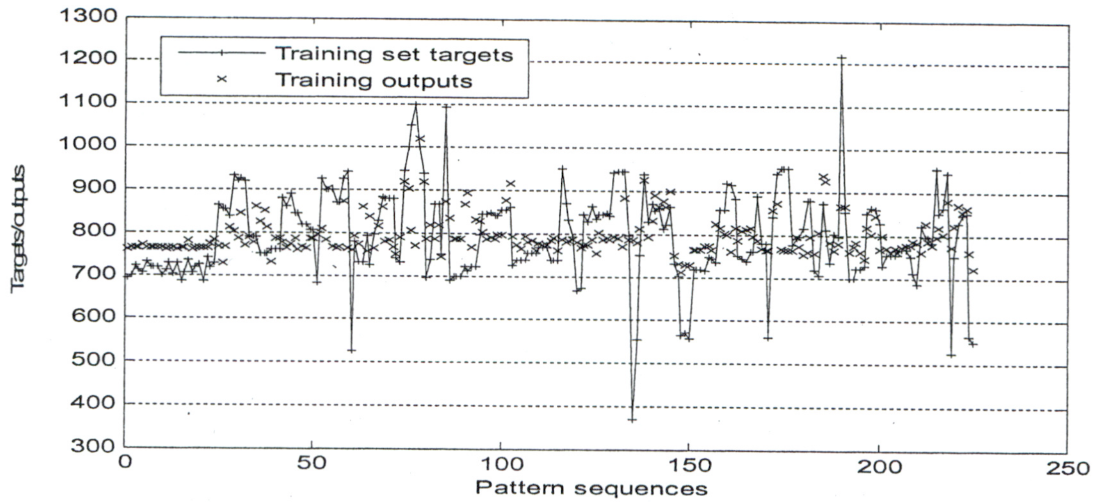


Fig. (4-d) Targets/outputs vs Pattern sequences (node 4-coarse agg.)

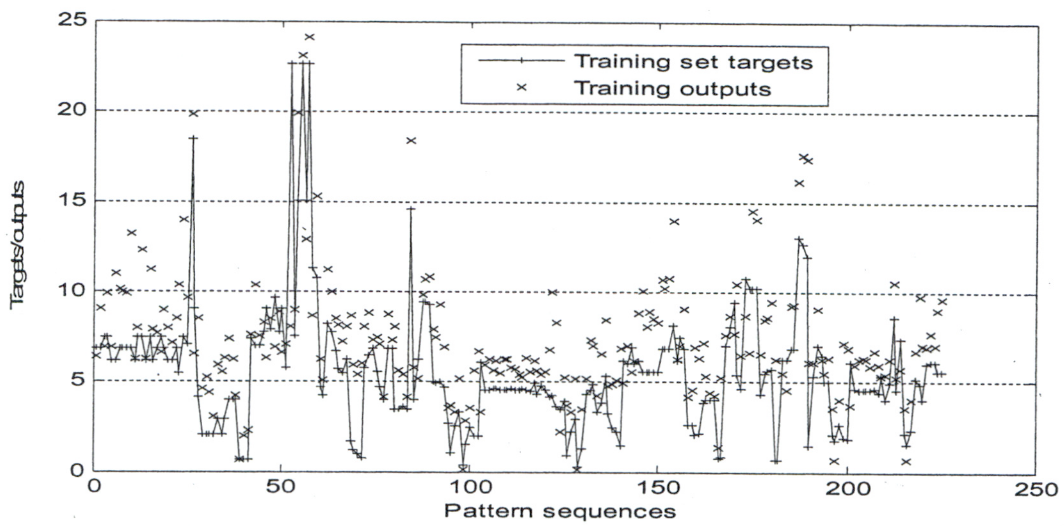


Fig. (4-e) Targets/outputs vs Pattern sequences (node 5-superplastisizer)

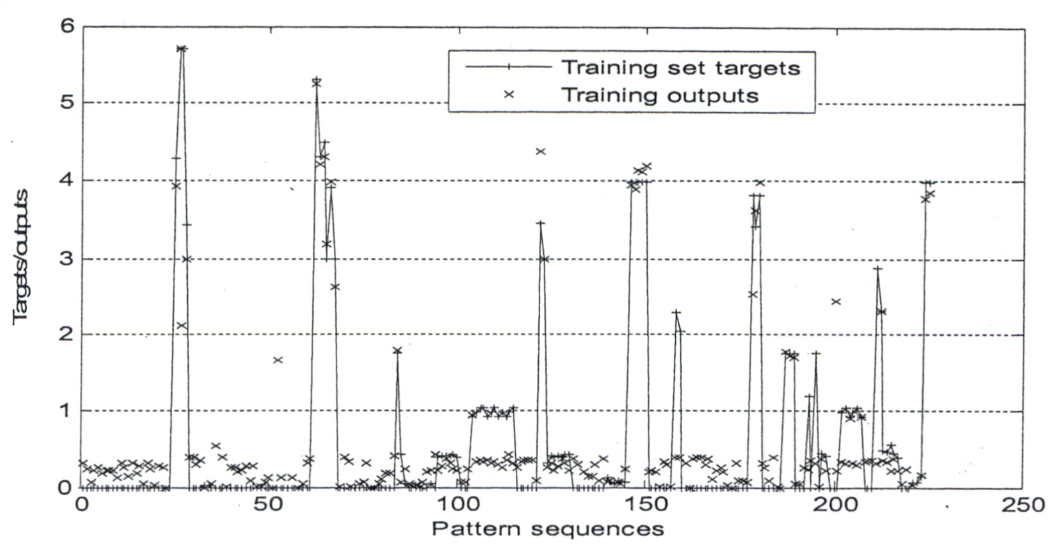


Fig. (4-f) Targets/outputs vs Pattern sequences (node 6-VEA)

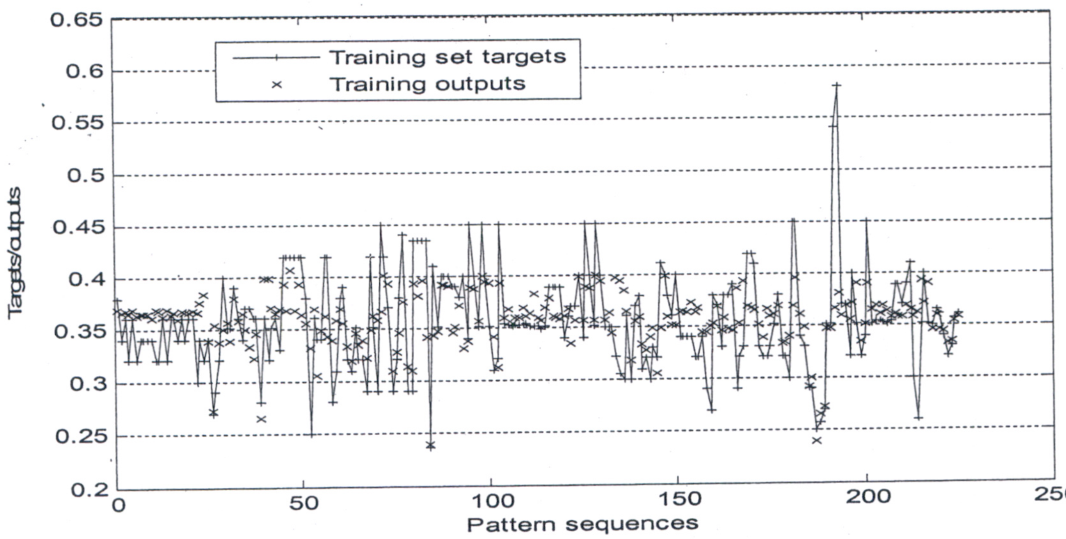


Fig. (4-g) Targets/outputs vs Pattern sequences (node 7-w/c)

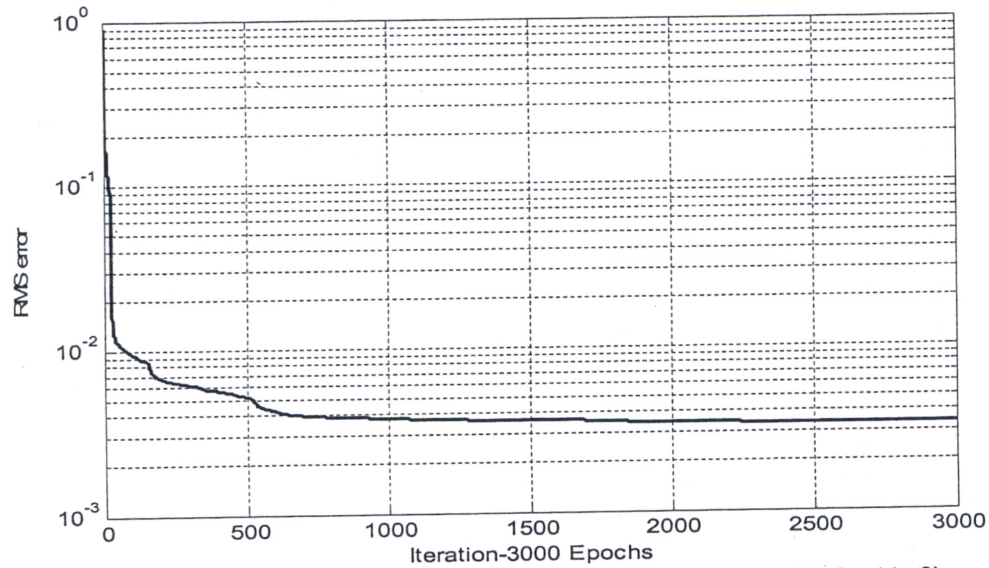


Fig. (5-a) Training RMS error- (Performance is 0.00338147, Goal is 0)

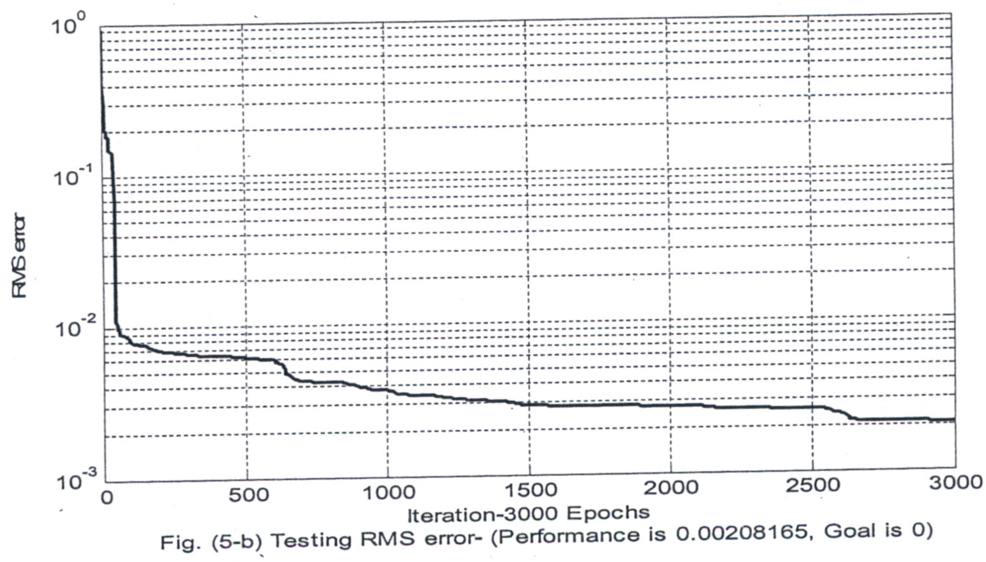


Fig. (5-b) Testing RMS error- (Performance is 0.00208165, Goal is 0)

**Table (3): Measured and predicted values of outputs variables for data sets used in testing of ANN model.**

| No | Testing data sets | | Experimental Mix | | | | | | | Mix from ANN program | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Fcu kg/cm2 | SF mm | C | P | FA | CA | SP | VEA | W/C | C | P | FA | CA | SP | VEA | W/C |
| 1 | 468 | 880 | 425 | 130 | 718 | 718 | 9.00 | 0.00 | 0.34 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 2 | 477 | 900 | 425 | 130 | 718 | 718 | 9.00 | 0.00 | 0.34 | 379 | 140 | 893 | 740 | 7.33 | 0.08 | 0.36 |
| 3 | 462 | 870 | 425 | 130 | 718 | 718 | 9.00 | 0.00 | 0.34 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 4 | 411 | 777 | 425 | 130 | 716 | 716 | 10.8 | 0.00 | 0.34 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 5 | 415 | 625 | 412 | 120 | 748 | 748 | 8.10 | 0.00 | 0.32 | 332 | 157 | 837 | 822 | 4.31 | 0.12 | 0.37 |
| 6 | 360 | 720 | 400 | 130 | 736 | 736 | 9.00 | 0.00 | 0.34 | 351 | 171 | 901 | 727 | 7.90 | 0.04 | 0.36 |
| 7 | 556 | 740 | 350 | 182 | 917 | 917 | 2.79 | 0.00 | 0.37 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 8 | 393 | 770 | 350 | 125 | 781 | 781 | 10.6 | 0.00 | 0.42 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 9 | 387 | 760 | 350 | 125 | 781 | 781 | 12.5 | 0.00 | 0.42 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 10 | 720 | 750 | 402 | 71 | 941 | 941 | 14.2 | 0.00 | 0.32 | 439 | 46 | 786 | 875 | 15.2 | 0 | 0.35 |
| 11 | 426 | 740 | 334 | 100 | 776 | 776 | 5.70 | 0.00 | 0.38 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 12 | 412 | 695 | .300 | 211 | 718 | 718 | 8.20 | 0.00 | 0.34 | 365 | 119 | 829 | 833 | 7.55 | 0.15 | 0.37 |
| 13 | 640 | 630 | 497 | 0 | 854 | 854 | 6.96 | 0.00 | 0.35 | 464 | 0 | 785 | 875 | 8.19 | 0 | 0.35 |
| 14 | 554 | 743 | 350 | 175 | 723 | 723 | 6.60 | 1.75 | 0.37 | 380 | 139 | 892 | 741 | 7.34 | 0.08 | 0.36 |
| 15 | 358 | 650 | 161 | 241 | 864 | 864 | 3.45 | 0.40 | 0.35 | 258 | 220 | 857 | 801 | 3.31 | 0.12 | 0.38 |
| 16 | 343 | 622 | 248 | 191 | 729 | 729 | 8.00 | 0.00 | 0.45 | 253 | 216 | 855 | 814 | 3.72 | 0.11 | 0.38 |
| 17 | 430 | 610 | 286 | 190 | 753 | 753 | 5.80 | 0.00 | 0.39 | 331 | 157 | 837 | 821 | 4.32 | 0.12 | 0.37 |
| 18 | 450 | 650 | 286 | 190 | 713 | 713 | 7.00 | 0.00 | 0.39 | 337 | 152 | 836 | 823 | 4.32 | 0.12 | 0.37 |
| 19 | 389 | 540 | 197 | 197 | 956 | 956 | 2.80 | 0.56 | 0.35 | 223 | 223 | 871 | 800 | 2.89 | 0.09 | 0.39 |
| 20 | 358 | 650 | 161 | 241 | 864 | 864 | 3.00 | 0.40 | 0.35 | 258 | 220 | 857 | 801 | 3.31 | 0.12 | 0.38 |

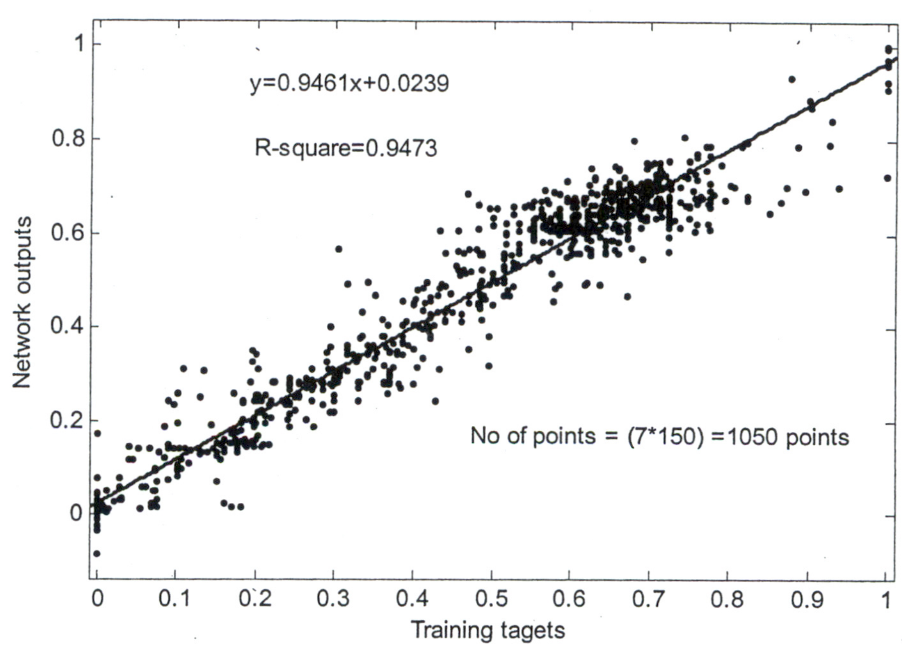


Fig. (6) Network outputs vs targets

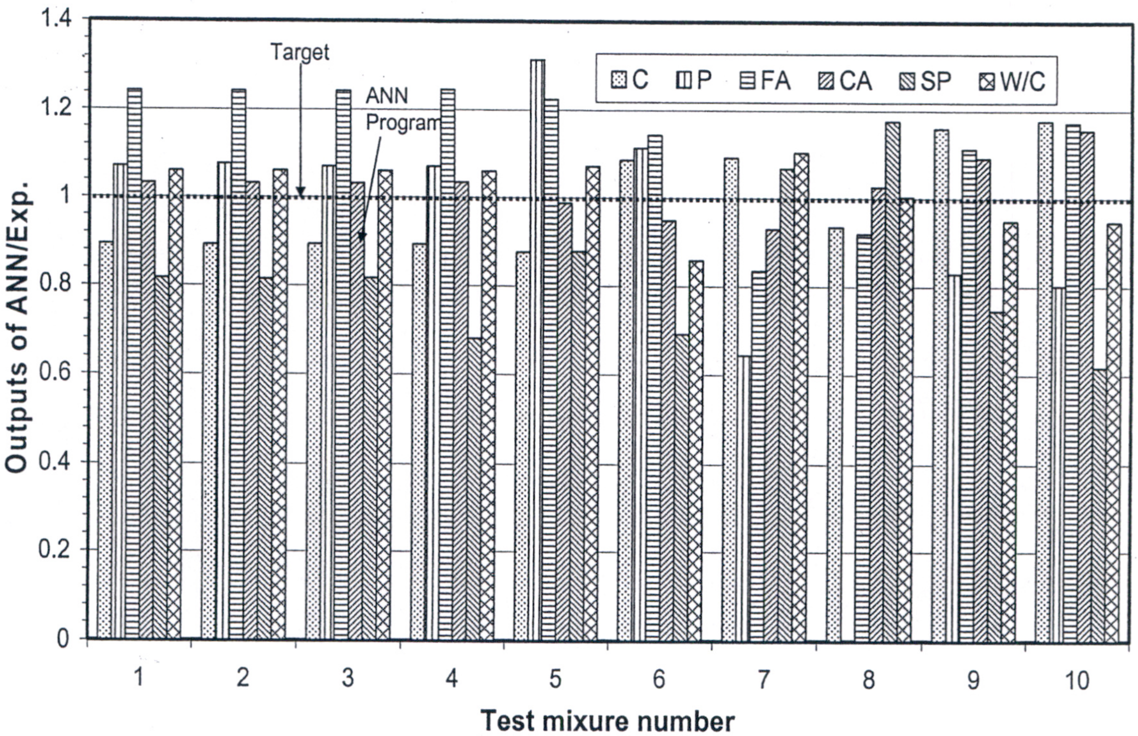


Fig. (7) Ratio mix design proportion (program/experimental)

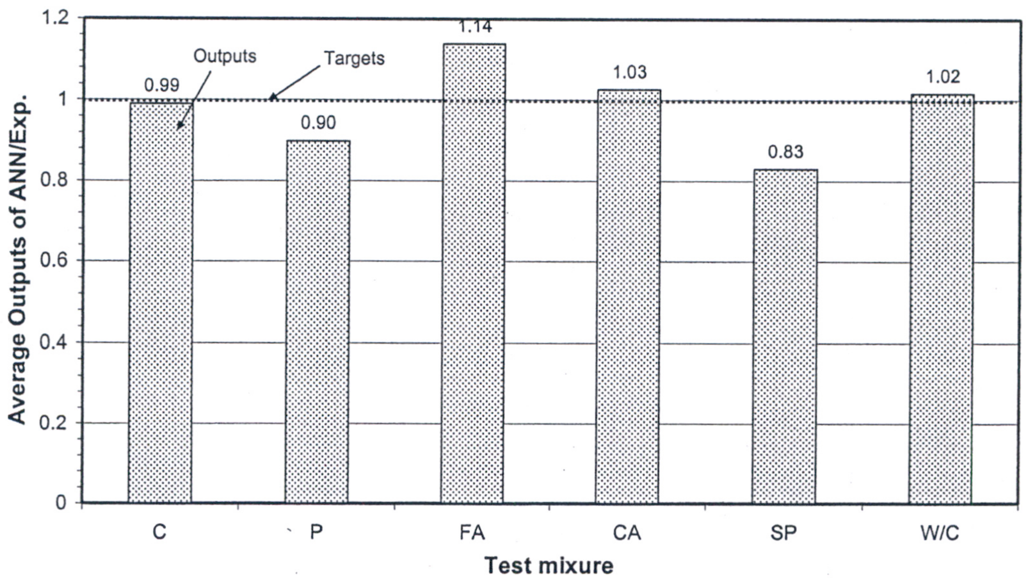


Fig. (8) Average Ratio mix design proportion (program/experimental)