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Prediction of Compressive Strength of Concrete using Artificial Neural Network

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ABSTRACT

Concrete cube strength determination tests are usually performed at three days to one year after pouring the concrete. The waiting period required to perform such test may delay the construction progress, decision making and neglecting such test would limit the quality control checks in large construction projects. Therefore it becomes necessary that the rapid and reliable prediction of concrete strength is essential for pre-design or quality control of construction. It is possible to facilitate the modification of the mix proportion if the concrete does not meet the required design stage, which may save time and construction costs. The early prediction of concrete strength is essential for estimating the desirable time for concrete form removal, project scheduling, quality control and estimating delay if any. Artificial Neural Network (ANN) is used to predict the compressive strength of concrete. Standard back propagation and Jordan–Elman algorithms are used to train the networks. Networks are trained and tested at various learning rate and momentum factor and after many trials these were kept constant for this study. Performance of networks were checked with statistical error criteria of correlation coefficient, root mean squared error and mean absolute error. It is observed that artificial neural networks can predict compressive strength of concrete with 91 to 98 % accuracy.

KEYWORDS: *Compressive strength, artificial neural networks, prediction*

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INTRODUCTION

Concrete is the most important element of the construction projects and it is most widely used because of its flow ability in the complicated form of the structural elements i.e. its ability to take any shape during wet in condition, and also its strength characteristics when it hardens. Concrete plain or reinforced with steel is used to build structures subjected to several extreme stress conditions. This composite material is obtained by mixing cement, water, fine and coarse aggregates in additions to admixtures in one form or others. Its production involves a number of operations according to prevailing site conditions. The ingredients of widely varying characteristics are generally used to manufacture concrete of acceptable quality standards. The strength, durability and other characteristics of concrete depends upon the properties of its ingredients, proportions of the mix, the method of compaction and other control measures. The attractiveness of concrete as a construction material is due to the fact that it is made from commonly available local ingredient material and can be used as per the functional requirements in a particular situation. The early prediction of concrete strength is most important due to quality and economic considerations essentially for determination of the desirable time for concrete form removal, project duration, quality control required and estimating delay in construction activities if any as development of mix design method plays a vital role in concrete construction. In this paper artificial neural network (ANN) is used to predict the compressive strength of concrete with standard back propagation and Jordan–Elman algorithms to train the networks.

LITERATURE REVIEW

Artificial neural network is the new promising tool to categorize and simplify the available experimental results due to its learning ability by examples. Concrete strength prediction can be mapped from the mix proportions. Concrete strength can be effectively modeled in a neural system in spite of deficiency in the data sets, it might be useful to the concrete mix design engineers and professionals as a new tool that may supports the decision making process and improved decision making. Literature is reviewed related to ANN and determination of compressive strength of concrete and same is discussed in the next section.

Kasperkiewicz[1] (1995) used artificial neural network of the Fuzzy-ARTMAP type for predicting strength properties of high-performance concrete (HPC) mixes. The 28-days compressive strength was considered the only intended for the prediction. A significant correlation between the actual strength and the predicted value by the neural network was observed. Results obtained suggested that the problem of prediction of concrete properties can be effectively modeled in a neural system, inspite of incomplete data. Yaqub et al.[2] (2006) gave mix design developed for high strength concrete with locally available constituents of concrete selected for the purpose of determining their relative quantities and proportions for the best outcome. Four mixes were used to achieve a compressive strength up to 162 Mpa. The variables were aggregate sizes and mix ratio. Four mix ratios by weight were selected with 0.30 water cement ratio in addition to this ultra727 super plasticizer was used to improve the workability of concrete mix. It was observed that the compressive strength depends on mix proportions, size and texture of aggregates and method of compaction. I-Cheng Yeh[3] (2006) found that fly ash and slag concrete is a highly complex material whose behavior is difficult to model and described a method of modeling slump of fly ash and slag concrete using artificial neural networks. The model built was examined with response trace plots to explore the slump behavior of fly ash and slag concrete. Author brings to a close conclusion that response trace plots can be used to explore the complex nonlinear relationship between concrete components and concrete slump. Noorzaei et al.[4] (2007) focused on development of artificial neural networks (ANNs) for prediction of compressive strength of concrete after 28 days. To predict the compressive strength of concrete six input parameters cement, water, silica fume, super plasticizer, fine aggregate and coarse aggregate were identified considering two hidden layers for the architecture of neural network. The performance of the 6-12-6-1 architecture was observed to be the best possible architecture. The results of the study indicated that ANNs have strong potential as a feasible tool for predicting the compressive strength of concrete. Mohammad et al.[5] (2009) reported the importance of the ingredient materials for producing high strength concrete (HSC) along with the results of an experimental study on achieving high strength concrete. Chou et al.[6] (2011) optimized the prediction accuracy of the compressive strength of high-performance concrete (HPC) by comparing data-mining methods. The compressive strength of high-performance concrete is observed to be a function of all concrete content, including cement, fly ash, blast-furnace slag, water, super plasticizer, age, and coarse and fine aggregate. The quantitative analyses in this study were performed by using five different data-mining methods i.e. artificial neural network, support vector machines, multiple regression, multiple additive regression trees and bagging regression trees. The methods were developed and tested against a data set derived from 17 concrete strength test laboratories. The cross-validation of unbiased estimates of the prediction models for performance comparison purposes indicated that multiple additive regression tree (MART) was superior in prediction accuracy, training time, and aversion to over fitting. Analytical results also suggested that MART-based modeling is effective for predicting the compressive strength of varying HPC age. Barbuta et al. (2012)[7] concludes the study conducted with neural networks for determining the properties of polymer concrete with fly ash. In their study polymer concrete with different contents of fly ash and resin was prepared and tested for determining the influence of fly ash on the properties. Using neural networks, the experimental results were analyzed for predicting the compressive strength and flexural strength and also on the basis of a model with given values of properties to ascertain the composition. This motivates the authors to use artificial neural network with two different training algorithms of standard error back propagation and Jordan- Elman type in the neural architecture. The next section describes the research objectives and methodology adopted in this paper.

OBJECTIVES OF STUDY

The objective of the study is to (a) understand existing methods of determining strength of concrete mix (b) study the factors responsible for the development of strength of concrete (c) develop a model based on Artificial Neural Network to predict strength of concrete. Next sections discuss research methodology adopted in this work and details of the analysis.

METHODOLOGY ADOPTED

As we have discussed earlier artificial neural network is the new promising tool to categorize and simplify the available experimental results due to its learning ability by examples and concrete strength prediction can also be mapped from the mix proportions using ANN. Data set is obtained from a University of California, Irvine (UCI) repository of data (Yeh 1998)[3] regarding mix design for different grades of concrete and their characteristic cube compressive strength. The data is divided in 8 sets, namely 3 days characteristic compressive strength, 7 days characteristic compressive strength, 14 days characteristic compressive strength, 28 days characteristic compressive strength, 56 days characteristic compressive strength, 90 days characteristic compressive strength, 100 120 and 180 days (in one group) characteristic compressive strength and 270, 360 and 365 days (in one group) characteristic compressive strength. All input and output data have been normalized by maximum value for each parameter so that the values lie between 0 to 1 for better comparison and avoiding influence of greater parameter. The output of the network is obtained in the form of normalized output which is then de-normalized to actual values by multiplying each value by corresponding normalizing factor as used for preparing the training set. Table 1 shows the input-output parameter used and Figure 1 shows the same in the form of neural network architecture. Network architecture used was feed forward neural network. A standard Stuttgart Neural Network Simulator (SNNS) software is used to train run the ANN. In this type of network connection is allowed from a node in layer 'i' only to nodes in layer 'i+1' as shown in the Figure 1. The standard back propagation and Jordan Elman back propagation algorithms are used to adjust the connection weights and bias values training. The network parameters tested in the proposed model included the following: training data = 60%, validation data = 20% and testing data = 20%, the number of hidden layers was 1, 2 and 3, the number of hidden neurons was 17 in each layer decided based on the experience and trial and error, the learning rate was 0.01, 0.1, 0.3, 0.5, and 0.9, the momentum factor was 0.01, 0.1 and 0.25 and the number of cycles used for training = 5000 and each cycle covers the entire data set available for training. Cycles for training were kept constant for all the training sets so as to have better comparison of the outcome of the networks. Integrated performance testing indicated that the best network parameters for both training algorithms were as follows: the number of input neurons = 8, the number of hidden layers = 1, the number of hidden neurons = 17, the number of output neurons = 1, the learning rate = 0.9 and the momentum factor = 0.01.

Table 1: Input output parameters

Sr. No.	**Input parameters (units)**	**Output parameter (units)**
1	Age (days)	Compressive Strength of concrete (Mpa)
2	Water (kg/m^3)	
3	Cement (kg/m^3)	
4	Super plasticizers (kg/m^3)	
5	Blast Furnace Slag (kg/m^3)	
6	Fly Ash (kg/m^3)	
7	Fine Aggregate (kg/m^3)	
8	Coarse Aggregate (kg/m^3)	

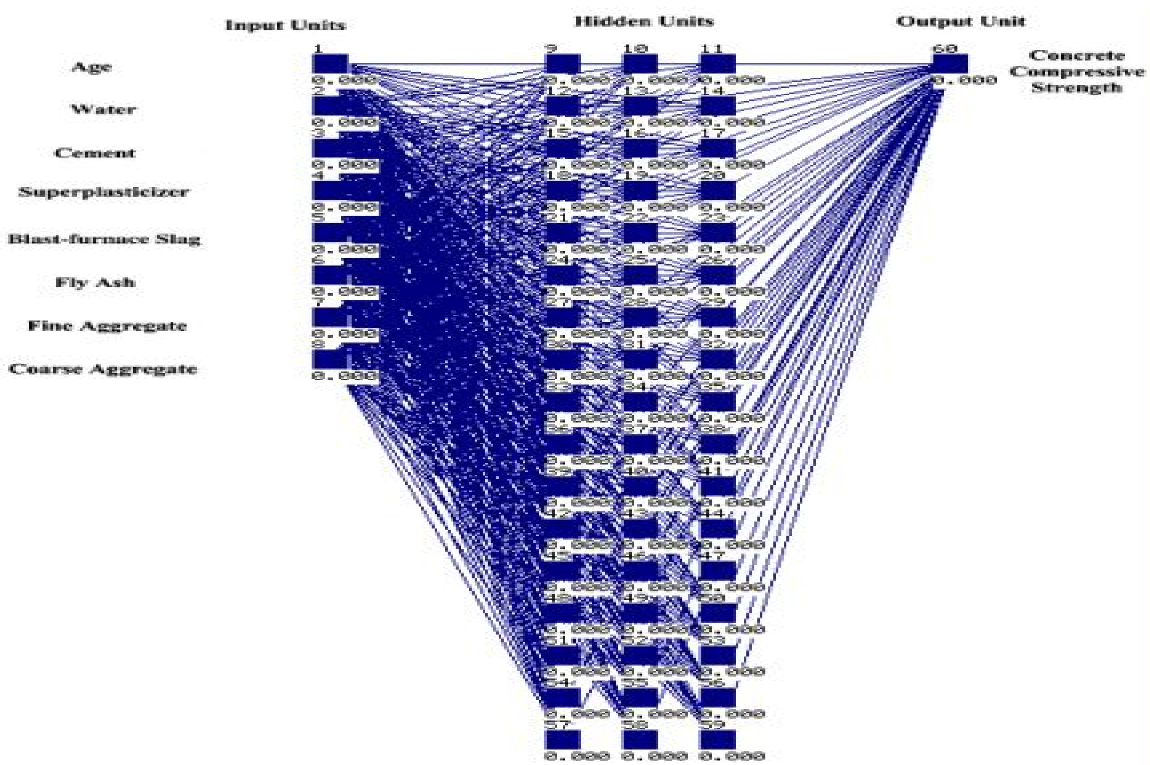


Fig.1. Neural network architecture

PERFORMANCE MEASURE

The performance measure of different techniques during training and testing was studied using the statistical error measures criteria's of correlation coefficient (r), root mean square error (RMSE) and mean absolute error (MAE). Details on the performance measures criteria can be seen in any standard text book of statistics and in brief it is discussed below:

(a) Correlation coefficient (r)

The correlation coefficient, R, measures the degree of linear association between the target and the realized outcome and it is a measure to know how far the trends in forecasted values follow those in actual observed values and it is a number between 0 to 1. Higher the correlation coefficient better is the model fit. The following formula was used to find the correlation coefficient (r):

$$r = \frac{\sum_{i=1}^{n}(x_i)(y_i)}{\sqrt{\sum_{i=1}^{n}(x_i^2)\sum_{i=1}^{n}(y_i^2)}} \qquad (1)$$

Where,

$x_i = X_i - \bar{X}$, $y_i = Y_i - \bar{Y}$

$X_i = i^{th}$ observed value, $\bar{X} = mean\ of\ X$,

$Y_i = i^{th}$ predicted value, $\bar{Y} = mean\ of\ Y$, n = number of observation of X_i and Y_i

(b) Root mean square error (RMSE)

The root mean square error is applicable to iterative algorithms and is a better measure for higher values. It offers a general representation of the errors involved in the prediction. The lower the value of RMSE, the better the fit is. The following formula is used to compute RMSE:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}} \qquad (2)$$

(c) Mean absolute error (MAE)

The mean absolute error has the advantage that it does not distinguish between the over and under-estimation and does not get too much influenced by higher values. It is generally engaged in addition to RMSE to get the average error without worrying about the positive or negative sign of the difference. Lower the value of MAE the better is the forecasting performance. The following formula is used to compute MAE:

$$MAE = \frac{\sum_{i=1}^{n}|X_I - Y_i|}{n} \qquad (3)$$

RESULTS AND DISCUSSION

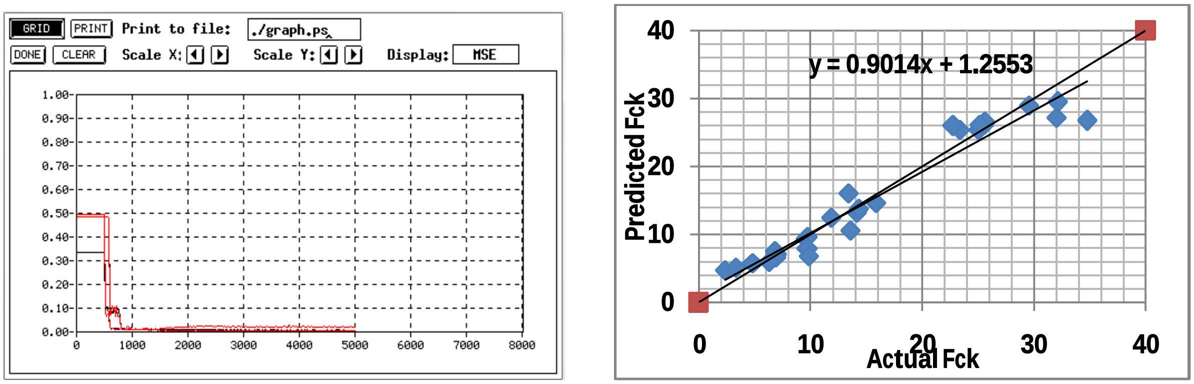
Trials were run for determination of compressive strength of concrete using artificial neural network. Table 2 gives the best results obtained, algorithm used, network size including input layer, hidden layer and output layer. As discussed earlier number of cycles, momentum rate, learning rate for the respective algorithm type along with the statistical performance measures of correlation coefficient, root mean squared error and mean absolute error are also given in the Table 2. It is observed that ANN proves its ability to perform better in prediction of compressive strength of concrete at 3, 7, 14, 28, 56, 90, 100, 120, 180, 360 and 365 days in terms of higher correlation coefficient (r) in the range of 0.91 to 0.98 and lower RMSE in the range of 1.72 to 5.77 Mpa and MAE 1.25 to 4.44 Mpa. Figure 2 to 17 shows MSE plot and scatter plot of actual vs. predicted compressive strength of concrete (F_{ck}) using standard error back propagation and Jordan-Elman algorithm for eight different combinations.

Table 2: Performance of artificial neural network

Sr. No.	Days	Algorithm	Network	No. Of Cycles	M.F	L.R	R	RMSE (Mpa)	MAE (Mpa)
1	3	BP	8-17-1	5000	0.01	0.9	0.97	2.38	1.66
		J-E					0.96	2.39	1.78
2	7	BP	8-17-1	5000	0.01	0.9	0.95	1.81	1.58
		J-E					0.95	1.86	1.66
3	14	BP	8-17-1	5000	0.01	0.9	0.93	1.72	1.25
		J-E					0.93	1.77	1.38
4	28	BP	8-17-1	5000	0.01	0.9	0.92	4.27	3.30
		J-E					0.91	4.72	3.60
5	56	BP	8-17-1	5000	0.01	0.9	0.96	3.61	3.07
		J-E					0.94	5.77	4.44
6	90	BP	8-17-1	5000	0.01	0.9	0.98	2.47	2.22
		J-E					0.98	2.24	1.81
7	100 120 180	BP	8-17-1	5000	0.01	0.9	0.98	2.45	1.83
		J-E					0.98	2.68	2.00
8	270 360 365	BP	8-17-1	5000	0.01	0.9	0.97	2.27	1.68
		J-E					0.97	2.30	1.74

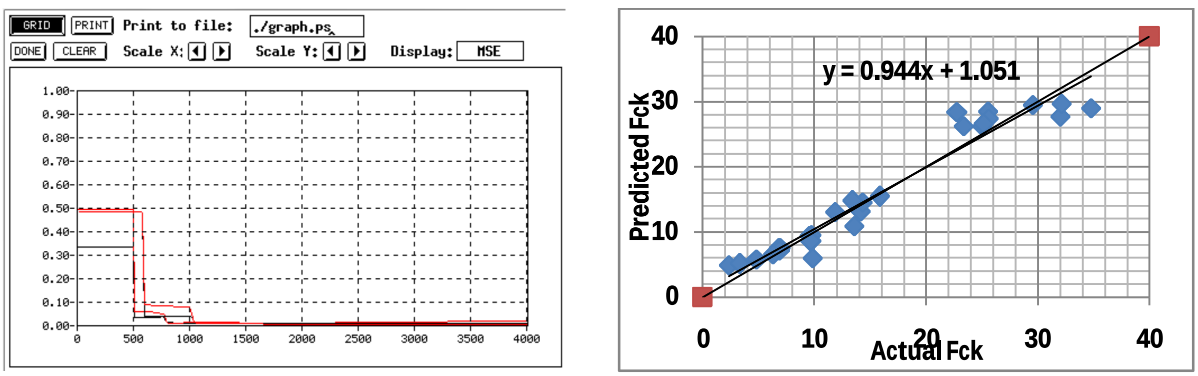
Figure 2 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 3 days using standard error back propagation and same is shown in Figure 3. (a) and (b) with Jordan-Elman algorithm. It shows that the error in training start reducing from 500/1000 cycles to negligible at 5000 cycles. It also indicates that the network is trained properly and testing of data set is done at this stage. Prediction of concrete strength at 3 days gives correlation coefficient, RMSE and MAE of 0.97, 2.38 Mpa and 1.66 Mpa using standard error back propagation whereas same is 0.96, 2.39 Mpa, 1.78 Mpa using Jordan- Elman algorithm. Standard error back propagation performs well as compare to JE algorithm. Similar to prediction of compressive strength of concrete at 3 days, prediction of concrete strength at 7 days is also determined using ANN. Figure 4 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 7 days using standard error back propagation and Figure 5. (a) and (b) with Jordan-Elman algorithm. In this case error in training reduced from 500/800 cycles to negligible at 5000 cycles and the network gets qualified suitably and hence data set is tested at this stage. The performance measures in terms of correlation coefficient, RMSE and MAE gives value of 0.95, 1.81 Mpa and 1.58 Mpa for standard error back propagation whereas same is 0.95, 1.86 Mpa, 1.66 Mpa for Jordan-Elman algorithm. Standard error back propagation performs better as compared to JE algorithm. Concrete strength at 14 days with BP and JE algorithm also shows better prediction and gives correlation coefficient, RMSE and MAE of 0.93, 1.72 Mpa and 1.25 Mpa with standard error back propagation and 0.93, 1.77 Mpa, 1.38 Mpa with Jordan- Elman algorithm. Standard error back propagation performs well as compare to JE algorithm. Figure 6 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 14 days using standard error back propagation and same is shown in Figure 7. (a) and (b) with Jordan-Elman algorithm. As compare to earlier two cases i.e. prediction of compressive strength of concrete at 3 and 7 days, 14 days compressive strength prediction is less accurate by both the algorithms. In general prediction of compressive strength of concrete at 28 days is more important in order to execute the construction activities. Figure 8 (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} by standard error back propagation and same is shown in Figure 9. (a) and (b) with Jordan-Elman algorithm at 28 days. The error in training starts reducing from 400 to 1000 cycles and becomes negligible at around 5000 cycles. Scatter plots shows that the prediction for higher values of F_{ck} is less accurate in case of both the algorithms compared to lower values of F_{ck}.. The scatter plotted with Jordan-Elman algorithms becomes wider as compared to standard error back propagation. Figure 10 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 56 days using standard error back propagation and same is shown in Figure 11. (a) and (b) with Jordan-Elman algorithm. It shows that the error in training start reducing from 500 to 800 cycles to negligible at 5000 cycles. Figure 12 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 90 days using standard error back propagation and same is shown in Figure 13. (a) and (b) with Jordan-Elman algorithm. JE performs well as compare to Standard error back propagation algorithm. Figure 14 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 100, 120, 180 days using standard error back propagation and same is shown in Figure 15. (a) and (b) with Jordan-Elman algorithm. In terms of the correlation coefficient both the training algorithms performed well but RMSE and MAE is lower in case of standard error back propagation than the JE. We can consider that Standard error back propagation is more reliable compared to JE. Figure 16 shows (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} at 270, 360, 365 days using standard error back propagation and same is shown in Figure 17. (a) and (b) with Jordan-Elman algorithm. It shows that the error in training start reducing from 500 to 1000 cycles to negligible at 5000 cycles. Standard error back propagation performs well as compare to JE algorithm. In almost all the cases i.e. from 3 days to 365 days standard error back propagation trains well compared to JE. This may be due to propagating error in the backward direction and retraining in the next cycles makes network more understandable.

Thus ANN gives an impression of being more suitable tool in prediction of compressive strength of concrete and can be looked upon as an alternative to the statistical tools.



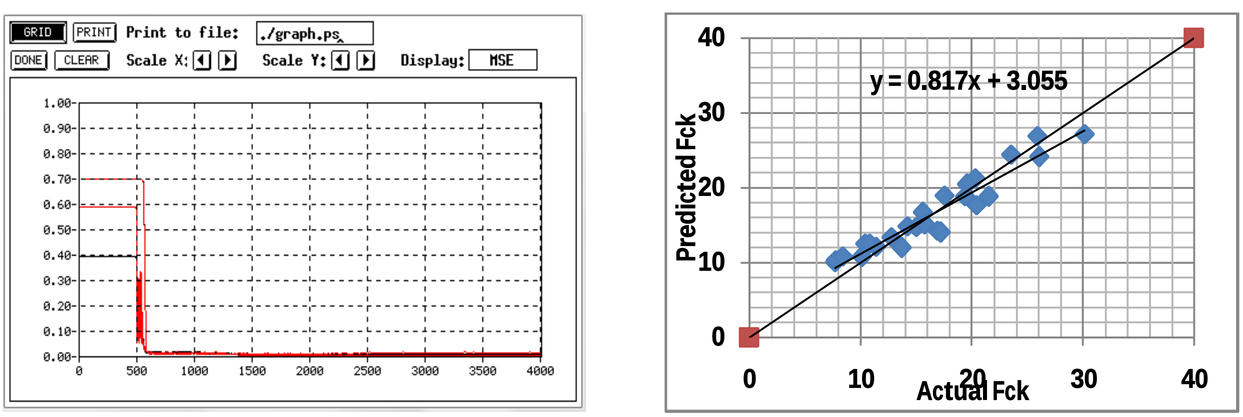
(a) (b)

Fig.2. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 3 days) using standard error back propagation



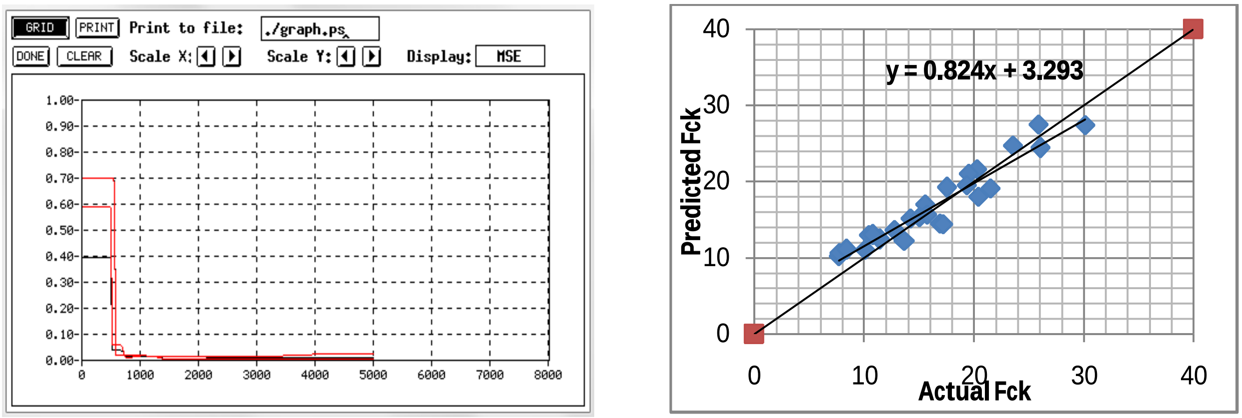
(a) (b)

Fig.3. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 3 days) using Jordan-Elman algorithm



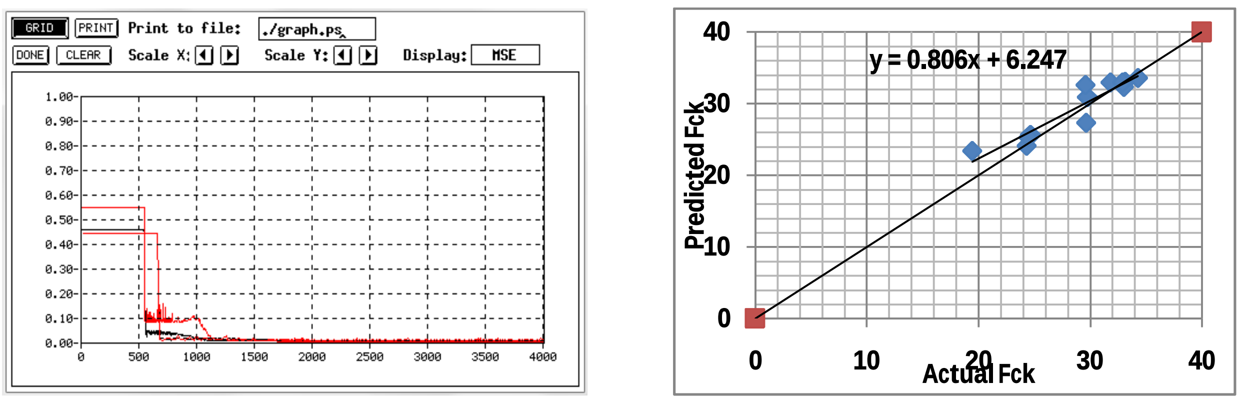
(a) (b)

Fig.4. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 7 days) using standard error back propagation



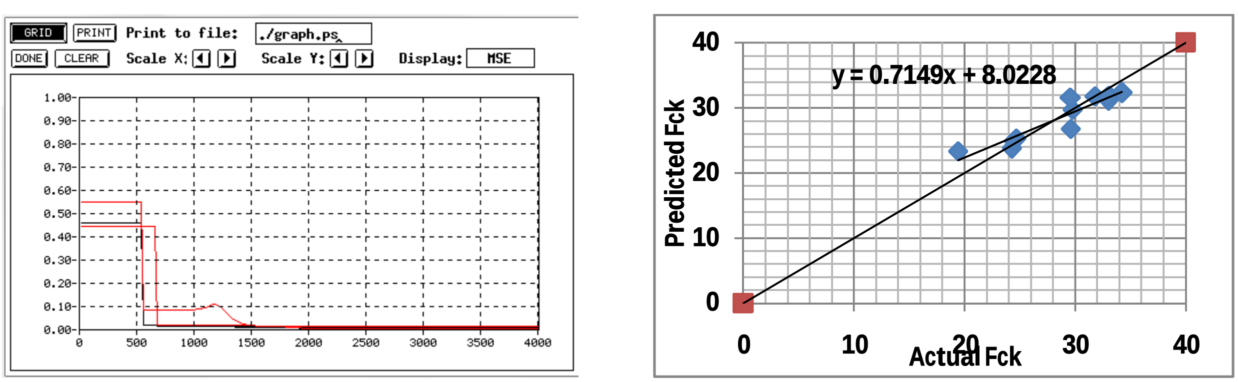
(a) (b)

Fig.5. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 7 days) using Jordan-Elman algorithm



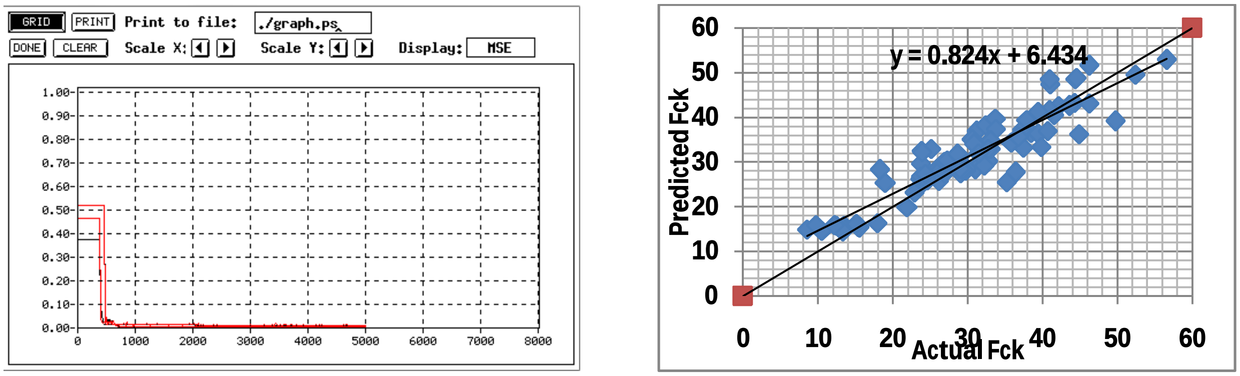
(a) (b)

Fig.6. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 14 days) using standard error back propagation



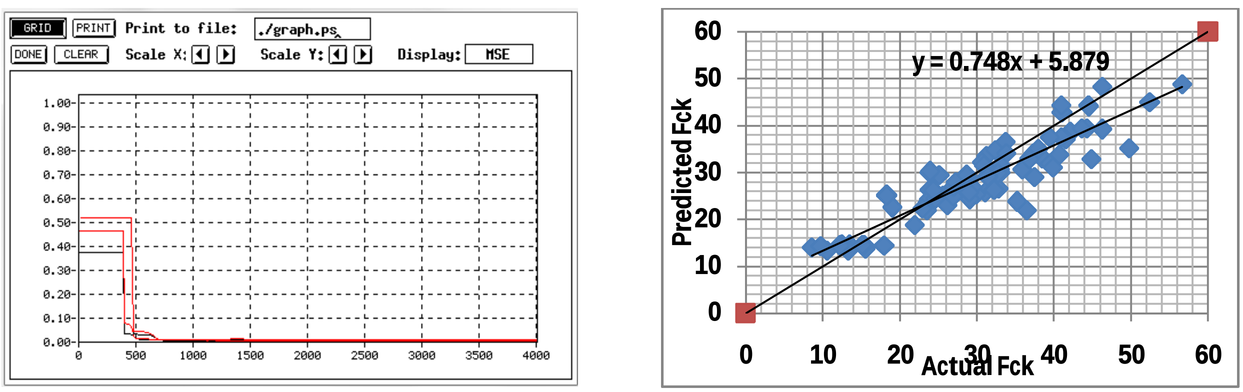
(a) (b)

Fig.7. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 14 days) using Jordan-Elman Algorithm



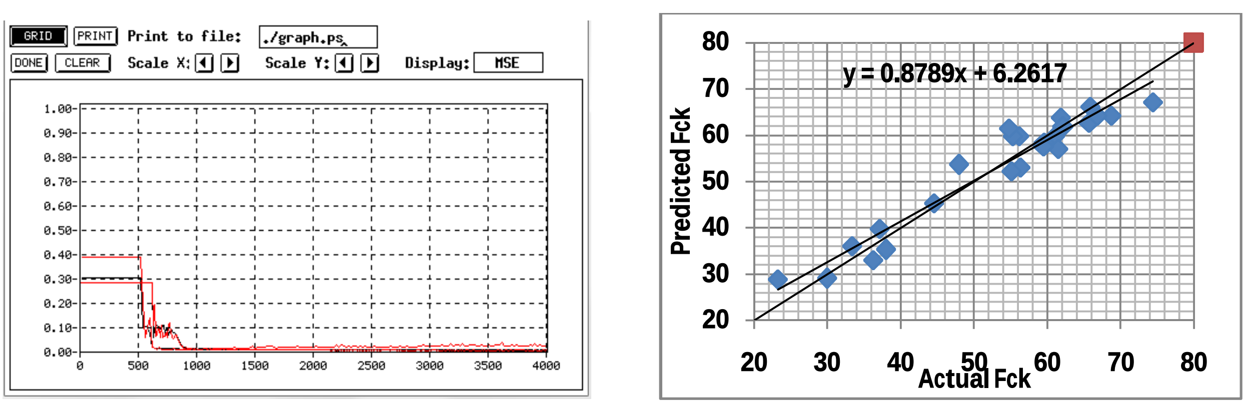
(a) (b)

Fig.8. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 28 days) using standard error back propagation



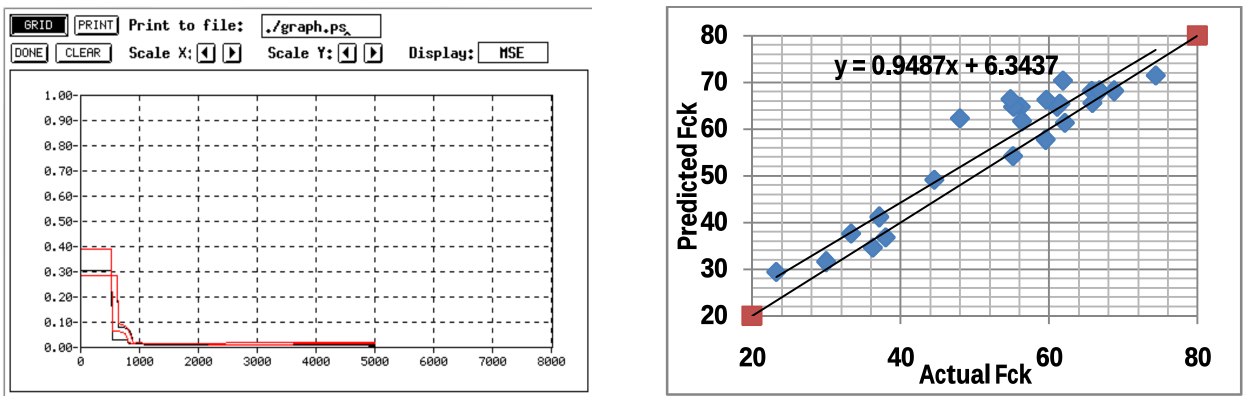
(a) (b)

Fig.9. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 28 days) using Jordan-Elman Algorithm



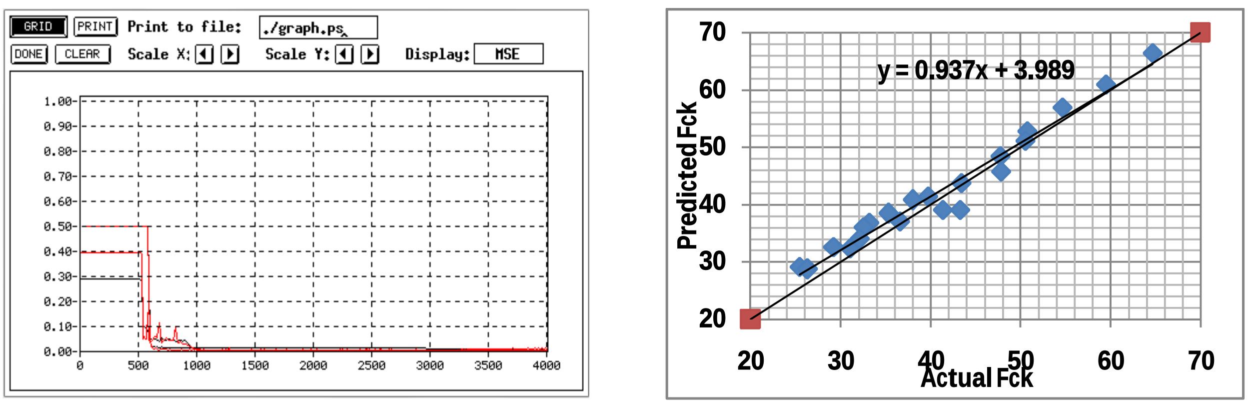
(a) (b)

Fig.10. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 56 days) using standard error back propagation



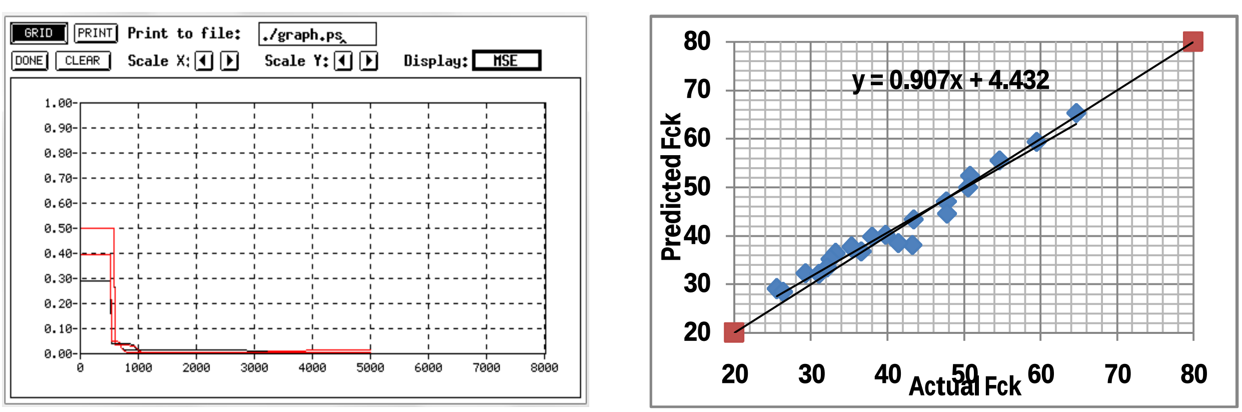
(a) (b)

Fig.11. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 56 days) using Jordan-Elman Algorithm



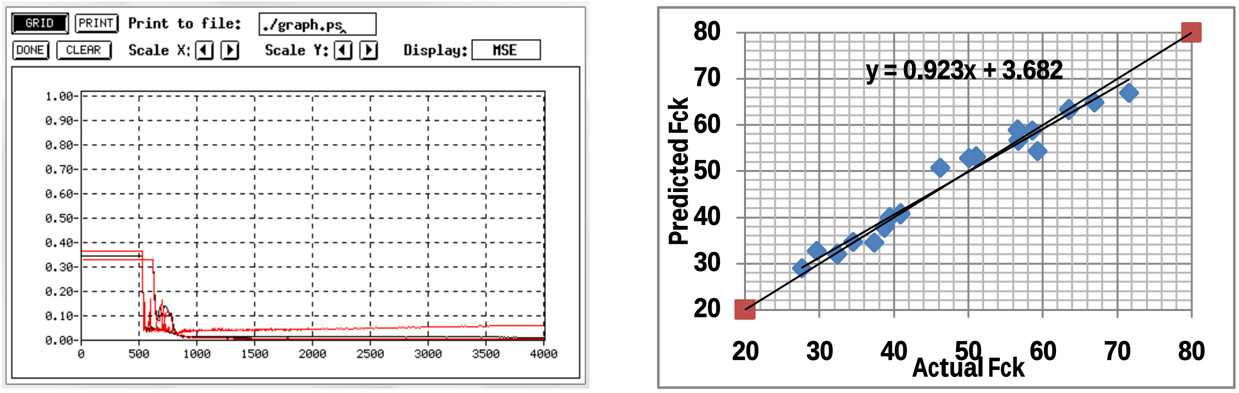
(a) (b)

Fig.12. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 90 days) using standard error back propagation



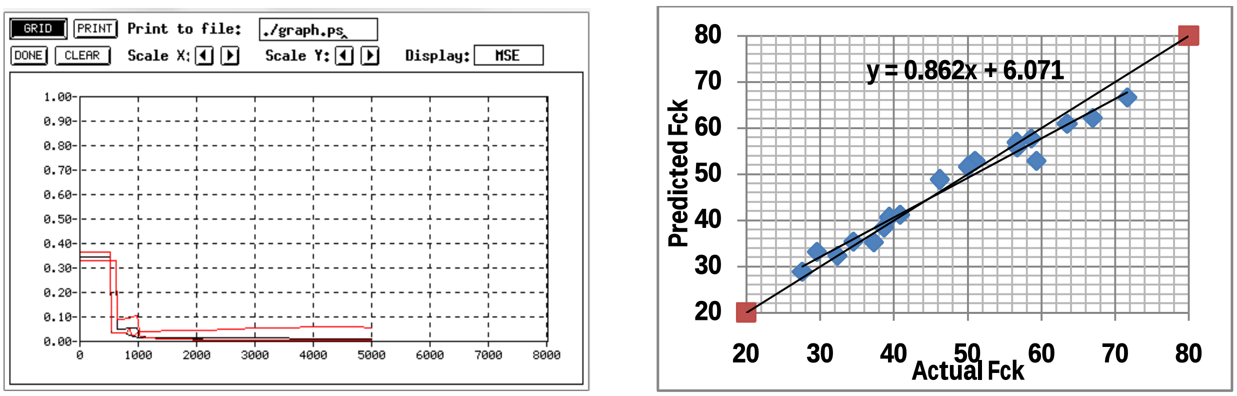
(a) (b)

Fig.13. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 90 days) using Jordan-Elman algorithm



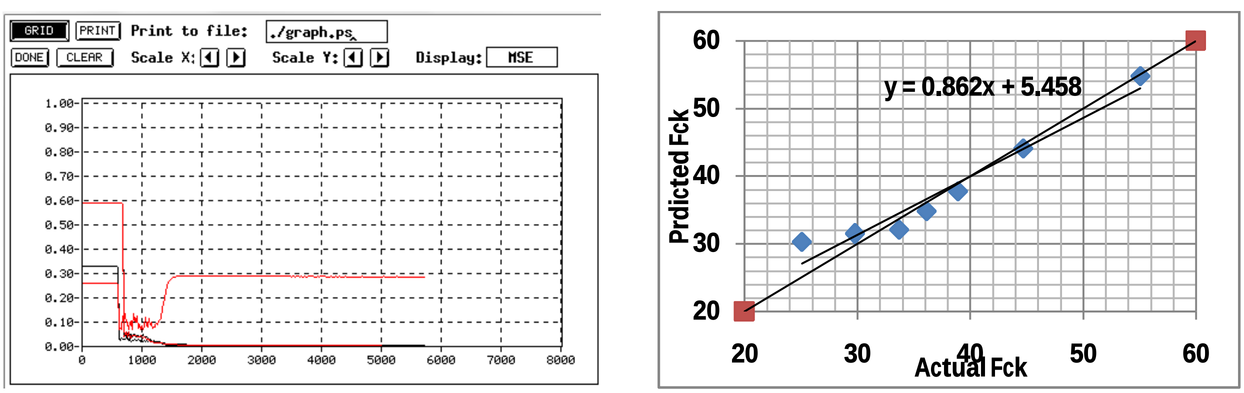
(a) (b)

Fig.14. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 100, 120 and 180 days) using standard error back propagation



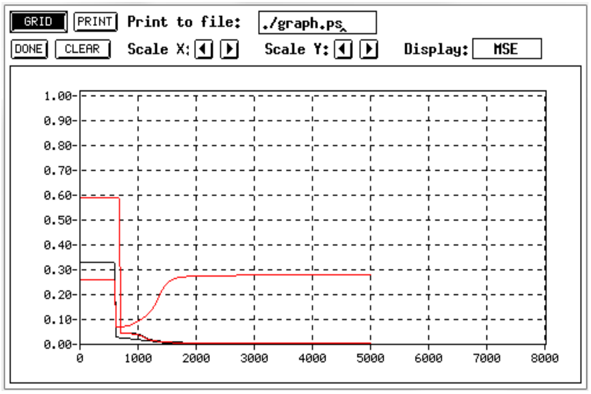
(a) (b)

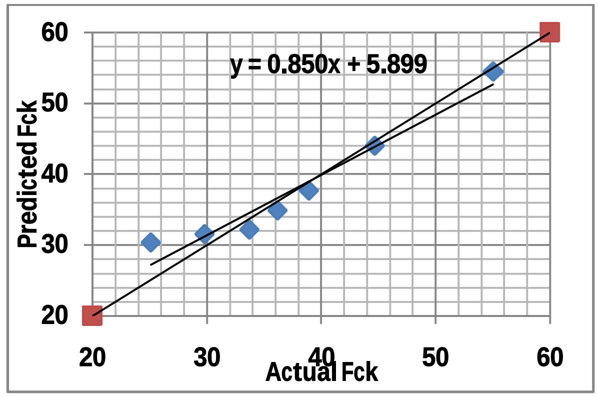
Fig.15. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 100, 120 and 180 days) using Jordan-Elman algorithm



(a) (b)

Fig.16. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 270, 360 and 365 days) using standard error back propagation





(a) (b)

Fig.17. (a) MSE plot and (b) scatter plot of actual vs. predicted F_{ck} (at 270, 360 and 365 days) using Jordan-Elman algorithm

CONCLUSIONS

This study developed a data-mining approach to predict compressive strength and assess the prediction reliability for high performance concrete. Artificial Neural Network was used. The proposed approaches were compared for performance outcomes by using three different performance measures (r, RMSE, MAE) to obtain a widespread comparison of the applied extrapolative techniques. The findings shows that predictions can be achieved with the best accuracy of correlation coefficient (r), root mean squared error (RMSE) and mean absolute error (MAE). It was observed that standard error back propagation works well in terms of higher r and lower RMSE and MAE compared to JE. ANN can be looked upon an alternative approach in prediction of concrete compressive strength.

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