ISSN: 0976-3031

Available Online at http://www.recentscientific.com

International Journal of Recent Scientific Research
Vol. 6, Issue, 5, pp.3872-3880, May, 2015

International Journal of Recent Scientific Research

RESEARCH ARTICLE

ANALITICAL STUDY ON COMPRESISVE STRENGTH OF REACTIVE POWDER CONCRETE

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ARTICLE INFO

Article History:

Received 2nd, April, 2015
Received in revised form 10th, April, 2015
Accepted 4th, May, 2015
Published online 28th, May, 2015

Key words:

Artificial Neural Networks (ANNs), Feed-Forward Back Propagation (FFBP), Compressive Strength, Root Mean Squared Error (RMSE).

ABSTRACT

This work focuses on development of Artificial Neural Networks (ANNs) in prediction of compressive strength of reactive powder concrete after 28 days. To predict the compressive strength of reactive powder concrete nine input parameters that are cement, water, silica fume, fly ash, Ground granulated blast Furnace slag, super plasticizer, fine aggregate, Quartz sand and steel fibres are identified. A total of 35 different data sets of concrete were collected from the technical literatures. Number of layers, number of neurons, activation functions were considered and the results were validated using an independent validation data set. A detailed study was carried out, considering single hidden layers for the architecture of neural network. The performance of the 9-3-1 architecture was the best possible architecture. The results of the present investigation indicate that ANNs have strong potential as a feasible tool for predicting the compressive strength of reactive powder concrete.

INTRODUCTION

Reactive Powder Concrete (RPC), also called Ultra-High Performance Concrete (UHPC), is a type of fibre reinforced cementitious composite. Silica is the major ingredient of reactive powder concrete. Reactive Powder Concrete can achieve compressive strength which ranges approximately of about 200MPa. Reactive Powder Concrete generates special economic benefits and builds structures that are strong, durable, and sensitive with the environment. A comparison of the physical, mechanical, and durability properties of RPC and HPC (High Performance Concrete) shows that RPC possesses better strength and lower permeability compared to HPC.

Artificial Neural Network

An artificial neural network (ANN) is a computational model that is inspired by the structure and functional aspects of biological neural networks. A neural network (NN) consists of group of artificial neurons interconnected to each other, and it processes information by using a connectionist approach to computation. In most cases ANN works as an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are based on non-linear statistical data modeling tools. They are mostly used to model complex relationships between inputs and outputs or to find patterns in data.

The basic strategy for developing a neural network-based model for material behavior is to train a neural network on the results of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the trained neural network will contain sufficient information about material's behavior to qualify as a material model. Such a trained neural network not only would be able to reproduce the experimental results, but also it would be able to approximate the results in other experiments through its generalization capability.

A compressive strength of reactive powder concrete is a major and important mechanical property, which is generally obtained by measuring concrete specimen after a standard curing of 28 days. Concrete strength is influenced by lots of factors. Some of these parameters include quality of aggregate, strength of cement, water content and water-to cement ratio. The traditional approach used in modeling the effects of these parameters on the compressive strength of concrete starts using experimental data to determine unknown coefficients in the equation.

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According to Rumelhart, there are eight components of a parallel distributed processing model in 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 by using available data to understand the underlying pattern. They consist of a series of layers with a number of processing elements within each layer. These layers can be divided into three layers namely 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 It requires high processing time for large neural networks. gives the output.

Richard and Cheyrezy (1995), developed an ultra high strength ductile concrete with the basic principles of enhancing the homogeneity by eliminating the coarse aggregate, enhancing the microstructure by post-set heat treatment and the tensile strength of concrete was increased by incorporating small, straight, high tensile micro fibre. Two types of concretes were developed and designated as RPC200 and RPC800, which had exceptional mechanical properties. The mean compressive stress obtained for RPC200 was 218MPa and forRPC800 was exceeding 600MPa. For RPC800, a value of 810 MPa has been obtained with a mixture incorporating steel aggregate. The concrete finds its applications in industrial and nuclear waste storage silos.

Serkan Subasi (2009) investigated the prediction of mechanical properties of cement containing class C fly ash by using artificial neural network and regression technique. Artificial neural network (ANN) methods were used for determining the flexural tensile strength and the compressive strength of the cement specimens. Experimental results were used in the estimation methods. Fly ash content (%), age of specimen (day) and unit weight (g/cm³) were used as input parameters and flexural tensile and compressive strengths (N/mm²) were used as output parameters. The developed models and Pthe experimental results were compared in the testing data set. As a result, compressive and flexural tensile strength values of mortars containing various amounts class C fly ash can be predicted in a quite short period of time with tiny error rates by using the multilayer feed-forward neural network models than regression techniques**.**

Maroliya and Modhera (2010) compared the mechanical properties of plain RPC with Recron-3s fibre (RSFRPC) and corrugated steel fiber (SFRPC)**.** Their results shows that compressive strength of SFRPC was 30% increased while in RSFRPC strength reduced by 19%. Flexural strength of SFRPC and RSFRPC in comparison to plain RPC was found that 60% and 40% higher.

Wankhade M W and Kambekar A R (2013) studied about the prediction of compressive strength of concrete using artificial neural network in which networks are trained and tested at various learning rate and momentum factor were kept constant after many trials. 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.

Bonneau O, Pouline C, Dugat, J, Richard, P, and Aïtcin, P. C. (1996) compared reactive powder concretes from theory to practice to achieve compressive strength between 200 and 800 MPa. RPC is obtained through an optimization of its grain size distribution by scaling down the maximum size of aggregate to 600 micrometer, by pressing it during the first hours following its casting, and by applying some very simple heat treatment. To demonstrate that the material can be produced almost everywhere, Bouygues Company of France and the University of Sherbrooke, Canada, produced two RPC batches in industrial conditions using locally available materials. Lavanya Prabha, J.K. Dattatreya, M. Neelamegam .M.V.Seshagiri Rao (2010) conducted a study on complete stress-strain curves from uniaxial compression tests**.** The test shows that the effect of material composition on the stress strain behavior and the toughness index were studied. The highest cylinder compressive strength of 171.3 MPa and elastic modulus of 44.8 GPa were recorded for 2% 13 mm length fibres. The optimum fibre content was found to be 3% of 6mm length or 2% of 13mm length fibres. A new measure of compression toughness known as MTI (modified toughness index) was proposed by them and it is found to range from 2.64 to 4.65 for RPC mixes. The present study analyse the factors responsible for the development of strength of concrete and develop a model based on Artificial Neural Network to predict strength of concrete.

Designing of ann models

General

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps where basic flow for designing neural network is shown in Fig.1.

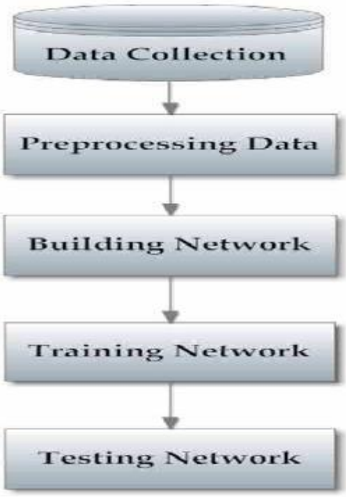


Fig. 1 Basic Flow for Designing Artificial Neural Network Model

Data Collection

In order to develop ANN architecture, 35 samples of concrete data on 28th day of compressive strength of reactive powder concrete were collected. In this, training, validation and testing sets were carries out. To test the reliability of the neural network model, 35 samples were selected. The process was carried out between the data had been statistically examined to ensure that it covers the range of input parameters.

These data's were collected for compressive strength of concrete after 28 days including weight per m^3 of each concrete. In a neural network if the area for data is more, learning is better. The accuracy of a neural network depends on the scattering of input information for training of the network. For this reason, classification of input information is very important in training. Therefore the input information is classified in six cases and in each case classification is based on one of the concrete components. The ranges of different parameters are in Table.1.

Development of Artificial Neural Networks

General

Artificial neural networks (ANNs) are categorized under artificial intelligence which, in their architecture, tries to simulate the biological structure of the human brain. ANNs try to imitate closely the behaviour of the basic biological and chemical processes of natural neural networks. ANNs learn by sample and therefore are well suited to complex processes, where the relationship between the variables is unknown. ANNs comprise of a number of artificial neurons (variously known as "processing elements", "PEs", "Nodes" or "Units"). Every processing element has several input paths and single output path, as shown in Fig..2.

Table.1 Data from Technical Literature

No.Of Samples	Cement	Silica Fume	Ggbs	Fly Ash	Quartz Sand	Fine Sand	Steel Fibres	SP	Water
Sample 1	1	0.25	0.00	0.00	0.33	0.77	0.00	0.00	0.27
Sample 2	1	0.14	0.33	0.30	0.33	2.22	0.28	0.07	0.30
Sample 3	1	0.30	0.00	0.00	0.35	1.29	0.11	0.05	0.25
Sample 4	1	0.30	0.00	0.00	0.35	1.25	0.22	0.05	0.25
Sample 5	1	0.30	0.00	0.00	0.35	1.21	0.34	0.05	0.25
Sample 6	1	0.32	0.00	0.00	0.36	1.50	0.02	0.03	0.22
Sample 7	1	0.00	0.00	0.00	0.00	1.76	0.06	0.10	0.18
Sample 8	1	0.15	0.00	0.00	0.00	1.76	0.06	0.10	0.18
Sample 9	1	0.30	0.00	0.00	0.00	1.76	0.06	0.10	0.18
Sample 10	1	0.00	0.00	0.00	0.00	1.64	0.05	0.10	0.18
Sample 11	1	0.15	0.00	0.00	0.00	1.64	0.05	0.10	0.18
Sample 12	1	0.30	0.00	0.00	0.00	1.64	0.05	0.10	0.18
Sample 13	1	0.00	0.00	0.00	0.00	1.54	0.05	0.10	0.18
Sample 14	1	0.15	0.00	0.00	0.00	1.54	0.05	0.10	0.18
Sample 15	1	0.30	0.00	0.00	0.00	1.54	0.05	0.10	0.18
Sample 16	1	0.20	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 17	1	0.23	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 18	1	0.25	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 19	1	0.27	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 20	1	0.30	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 21	1	0.32	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 22	1	0.30	0.00	0.00	0.35	1.50	0.00	0.03	0.20
Sample 23	1	0.30	0.00	0.00	0.35	1.50	0.00	0.03	0.22
Sample 24	1	0.30	0.00	0.00	0.35	1.50	0.00	0.03	0.23
Sample 25	1	0.27	0.00	0.00	0.35	1.55	0.00	0.03	0.30
Sample 26	1	0.27	0.00	0.00	0.35	1.55	0.00	0.03	0.22
Sample 27	1	0.18	0.29	0.00	0.00	1.47	0.00	0.03	0.22
Sample 28	1	0.18	0.29	0.00	0.00	1.47	0.05	0.03	0.22
Sample 29	1	0.25	0.00	0.00	0.00	1.25	0.00	0.03	0.16
Sample 30	1	0.25	0.00	0.25	0.00	1.50	0.10	0.05	0.18
Sample 31	1	0.25	0.00	0.00	0.00	1.25	0.17	0.03	0.16
Sample 32	1	0.33	0.00	0.67	0.00	2.00	0.27	0.05	0.25
Sample 33	1	0.32	0.00	0.00	0.00	1.50	0.00	0.03	0.20
Sample 34	1	0.32	0.00	0.00	0.36	1.50	0.02	0.04	0.22
Sample 35	1	0.32	0.00	0.00	0.36	1.50	0.02	0.03	0.22

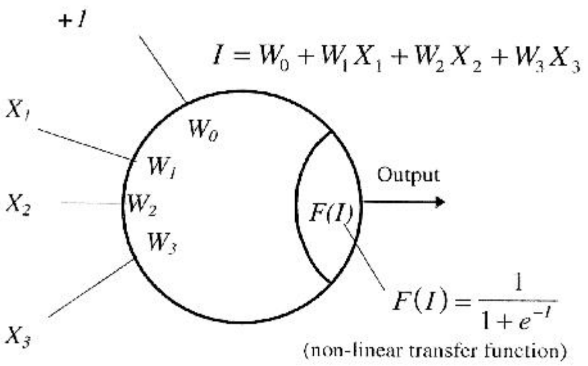


Fig. 2 Typical processing elements (PE) in a neuron

An individual PE receives its inputs from many other processing elements via weighted input connections. These weighted inputs are summed and passed through a transfer function to produce a single activation level for the processing element, which is the node output.

Architecture Of Neural Networks

On the basis of a review of the literature the following feed forward error back propagation networks are selected

- The network with momentum and the descent gradient (GDM)

- The network descent gradient with adaptive learning rate (GDA)
- The Levenberg-Marquardt network (LM)

While training the network optimum numbers of neurons in the hidden layer and learning rate were calculated. The neural network learnt to identify the compressive strength of concrete cube samples. The training phase is stopped when the variation of error became sufficiently small. The ANN model is then tested and the results are compared by means of root mean squared error and coefficient of determination.

A typical structure of ANN includes many processing elements that are arranged in layers: an input layer, an output layer, and one or more layers in-between, called intermediate or hidden layers are shown in Fig.3. Each processing element in a specific layer is interconnected to all the processing elements in the next layer via weighted connections. The scalar weights determine the strength of the connection between interconnected neurons. A zero weight indicates no connection between two neurons and a negative weight refers to a prohibitive relationship. The information navigates from the input layer where the input data are presented. The inputs are weighted and received by each and every node in the next layer. The weighted inputs are then added and passed through a non-linear transfer function to produce the node output, which is weighted and passed to the processing elements in the next layer. The network's output value is compared with the actual value and the error between the two values is calculated. This error is then used to adjust the weights until the network can find a set of weights that will produce the input-output mapping with the smallest possible error.

Feed-Forward Networks

In feed-forward networks (FFNs), the signals from the input neurons to the output neurons flow only in one direction. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs are straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as top-down. The information distribution is parallel for all the nodes of the succeeding layer.

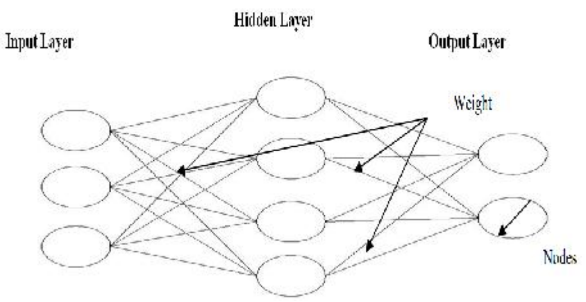


Fig. 3 Typical Structure of ANN Model

Feedback Networks

Feedback networks (FNs) can have signals travelling in any direction by introducing loops in the network. Though feedback networks are very powerful, it can become extremely complicated. FNs are dynamic and change continuously until they reach an equilibrium point. They stay at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are known for interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

Transfer Function

Depending upon the type of input data and the output required, there are five types of activation functions used to transform input signal into output viz., linear function, threshold function, sigmoid function, hyperbolic tangent function and radial basis function. Some of the important transfer functions are described below:

Linear output neurons are used for function fitting problems. The linear transfer function is shown in (Fig.4 a). For linear units, the output activity is proportional to the total weighted output. Thus, the algorithm is given in equation 1.

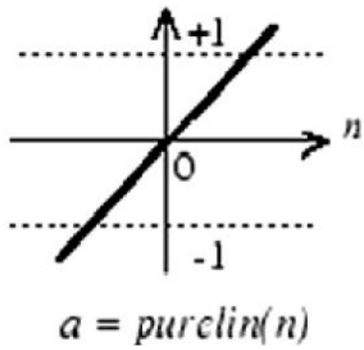
$$f(s) = s \qquad (1)$$

In case of the threshold units, the outputs are set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For example, if S_t is the threshold value then for all $s > s_t$, the neural network will output a value of 1 and for all other values it will output a value of 0 (Fig. 4 b). The equation 2 shows the threshold function,

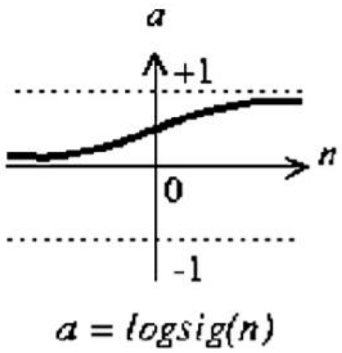
$$f(s) = \begin{cases} 1, \text{if } s > S_t \quad 0, \text{otherwise} \end{cases} \qquad (2)$$

For the sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations. The sigmoid function transforms the input into a value between 0 and 1. The log sigmoid function transforms any value of the input data from positive infinity and negative infinity to a value between zero and one.

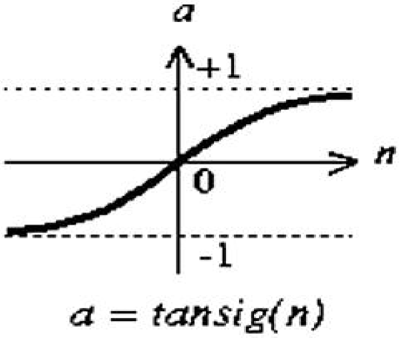
The function logsig generates outputs between zero and one as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function tansig. The functions are shown in (fig.4 c) which is shown below.



A Linear



B Log-sigmoidal



C Tan – sigmoidal

Fig. 4 Transfer Functions

The sigmoid transfer functions are used in the present study. To construct a neural network that performs some definite task, one must choose how the units are connected to one another and must set the weights on the connections appropriately. The connections conclude whether it is possible for one unit to influence another. The weights specify the strength of the influence.

Network Training Algorithm

The system learns new knowledge by adjusting the connection weights. The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training. The training method usually consists of one of the three schemes

- Unsupervised learning where no example outputs are provided to the network against which it can measure its predictive performance for a given set of inputs. The hidden neurons must find a way to organize themselves without help from the outside.
- Reinforcement learning where the relations among the neurons in the hidden layer are randomly arranged, then reshuffled. Reinforcement learning is otherwise termed as supervised learning, because it requires a teacher. The teacher can be a training set of data or an observer who grades the performance of the network results. Both reinforcement and unsupervised learning process suffers from relative slowness and inefficiency relying on a random shuffling to find the proper connection weights.
- Back propagation method is well-established and highly successful in training of multi-layered neural nets. The network is not just given reinforcement for how it is performing on a task. Information about errors is also filtered back through the system and is used to adjust the connection weights between the layers, thus improving performance.

Development of Ann Model

The various steps in developing a neural network model are

1. ***Variable selection:*** - The input variables important for modeling. Variables under study are selected by suitable variable selection procedures.
2. ***Formation of training, testing and validation sets:-*** The data set is divided into three distinct sets called training, testing and validation sets. The training set is the largest set and is used by neural network to learn patterns present in the data. The testing set is used to evaluate the generalization ability of trained network and final check on the performance of trained network is made using validation set.
3. ***Neural network architecture:-***Neural network architecture defines its structure including number of hidden layers, number of hidden nodes and number of output nodes and aictvation function.
4. ***Evaluation criteria:-***The most common error function minimized in neural networks is the mean squared errors.
5. ***Neural network training:-***The objective of training is to find the set of weights between the neurons that determine the global minimum of error function. This involves decision regarding the number of iteration, selection of learning rate a constant of proportionality which determines the size of the weight adjustments made at each iteration) and momentum value.

Construction of Neural Network Model And Parameters

The architecture of a network describes how many layers a network has, the number of neurons in each layer, each layer's activation function, and how the layers connect to each other. The best architecture to use depends on the type of problem to be represented by the network. Selecting an optimal ANN architecture is an open problem of investigation and depends on the application domain. In the present study there are six inputs and compressive strength of concrete is output. For this reason, the initial structure of neural network is illustrated Figure 1. The architecture of neural network was determined by training, testing and validation.

Artificial Neural Network Based Analysis

The purpose of this investigation is to check the applicability of the ANN –based methodology to predict the compressive strength of reactive powder concrete. MATLAB software is used in developing the ANN models.

Input and Output

Experimental studies indicated that the strength is influenced by water, cement, fly ash, silica fume, Ground Granulated Blast Furnace Slag, Fine aggregate, Quartz sand Steel fibres and Superplasticiser. These nine parameters are used as input terminals in the input layer. The outputs of the ANN are compressive strength and these are tabulated in Table.2.

Table2 Input Output Parameters

S.No	Input Parameters	Output Parameters
1.	Cement	Compressive strength of Reactive powder concrete.
2.	Water	
3.	Silica fume	
4.	Super plasticizers	
5.	Blast Furnace Slag	
6.	Fly Ash	
7.	Fine Aggregate	
8.	Quartz sand	
9.	Steel Fibres	

Architecture of Ann

In the present study, three layers have been used that includes one input layer, one hidden layer and one output layer. The transfer functions 'tansig' is used in between the layers. The algorithm of the transfer functions used in MATLAB for tan-sigmoidal functions.

Training Of Ann

A single-layer network to perform a particular task can be explained by using the following procedure:

- Provide the network with training examples, which consist of sample activities for the input units together with the desired pattern of activities for the output units.
- Find out how closely the actual output of the network matches the desired output.
- Change the weight of each connection, so that the network produces a better approximation of the desired output.

Training of the neural network is carried out using 35 data sets. It is worth mentioning that in this study, the training process was terminated when any of the following conditions are satisfied

1. The maximum number of iterations is reached to 2500.
2. The mean square error of the training set is reached to 0.007.
3. The mean square error of the training data sets starts diverges after 800 number of iteration.

One of the important variables in network design is the learning rate coefficient. Each time a pattern is presented to the network, the weights leading to a neuron are modified slightly during learning in the direction required to produce a smaller error at the outputs the next time the same pattern is presented. The amount of weight modification is proportional to the learning rate. The value of learning rate ranges between 0.0 and 1.0, where a value closer to 1 indicates significant modification in weight while a value closer to 0 indicates little modification.

However, the learning rate in a parameter that determines the size of the weights adjustment each time the weights are changed during training. Small values for the learning rate cause small weight changes and large values cause large changes. The best learning rate is not obvious. If the learning rate is 0.0, the network will not learn. The learning rate is very important in identifying over-learning and when to stop training.

In process of training, it was seen that for the range of (0.05-0.1) the learning rate, convergence was faster and number of iterations was less than other range. However, when the learning rate increased, the iterations number jumps to a divergence point and training doesn't converge even in 2500 training iterations. The effect of the learning rate was examined. The ANN model trained against different network functions shown in Fig.5.

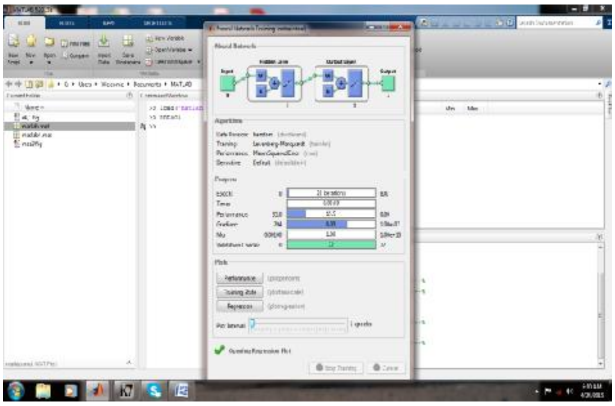


Fig.5 Typical Screen during Training Shot of ANN Model

Testing Of Ann

Next step after training process in the development of the ANN is to test the developed ANN model. Evaluate the confidence in the performance of the trained network with a training set for a 2500 number of iterations. The testing process has been carried out for a total 35 data sets with different training functions. Table 3 exhibits the comparison between predicted compressive strength of concrete against the experimental evidence, which highlighted that there is a good agreement between the predicted values and that of experiment data. The results are shown that the artificial neural network was very successful in predicting of compressive strength of error with RMSE. Also the ANN predicts the compressive strength of concrete in testing stage reasonably well the 9-3-1 neural models in general performs better than the others and it is able to give accurate prediction of compressive strength of concrete. It can be observed that the predicted values of compressive strength are in good agreement with those of the experimental values. Hence the developed models are robust and reliable. The result is converged at 2500 epochs.

Validation Of Ann

The validation set is used to as a further check for the generalization of the Neural Network, but do not have any effect on the training. In the validation phase, the ANN accuracy is examined using the validation set. The plot of predicted compressive strength of concrete in validation sets against experimental data depicted is shown in Fig.6. It is obvious from this plot that is reasonably good agreement between the results predicted and target results. These results show that the artificial neural network was successful in training the relationship between the input and output data.

Table 3 Experimental Observations and the Corresponding ANN Predicted Values with different Functions

No.of samples	Observed Compressive Strength	TRAINLM	GDX	GDM
Sample 1	97	97	178	177
Sample 2	106	106	178	137
Sample 3	150.4	156	178	176
Sample 4	168.5	161	178	175
Sample 5	156.5	166	178	172
Sample 6	151	151	156	177
Sample 7	72.5	75	94	177
Sample 8	100	102	117	176
Sample 9	119	128	148	175
Sample 10	75.5	75	85	177
Sample 11	115	114	98	176
Sample 12	138.5	132	124	175
Sample 13	78.5	79	82	177
Sample 14	128.5	130	93	176
Sample 15	128.5	136	115	175
Sample 16	93	88	103	177
Sample 17	95	96	108	177
Sample 18	97	103	111	177
Sample 19	115	111	115	177
Sample 20	116	123	121	177
Sample 21	121	130	125	177
Sample 22	126	143	129	177
Sample 23	141	136	116	177
Sample 24	135	132	111	177
Sample 25	81	83	86	177
Sample 26	125	111	115	177
Sample 27	125.5	125	73	175
Sample 28	133.9	134	75	175
Sample 29	163	160	73	176
Sample 30	170	171	178	174
Sample 31	178.2	176	74	174
Sample 32	172.2	173	178	144
Sample 33	106	105	73	176
Sample 34	151	155	178	175
Sample 35	151	151	156	177

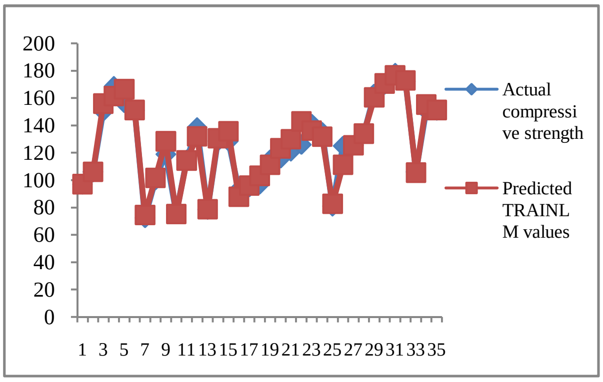


Fig.6 Plot of Predicted Compressive Strength against Observed Experimental Data

Comparison Of Training, Testing And Validation

The progress of the training was checked by plotting the training, validation and test mean square error versus the performed number of iterations, as presented is shown in Fig.7. The results in Figure indicate that the neural network was successful in learning the relationship between the different input parameters and output (compressive strength). Depending on the way in which the neurons are connected, three types of artificial neural networks are distinguished: unidirectional networks, cellular networks and recursive networks.

Comparison Of Experimental Vs Predicted Strength

The observed experimental strength was compared with different network functions namely GDX, GDM, LM and thus TRINLM gives best accuracy result when compared with the other are shown in Figs.8 to 14.

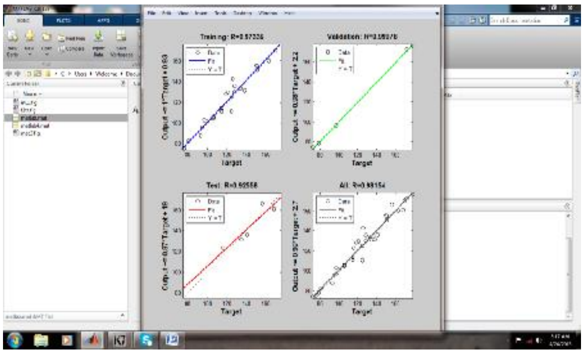


Fig.7 Comparison of Training, Testing and Validation

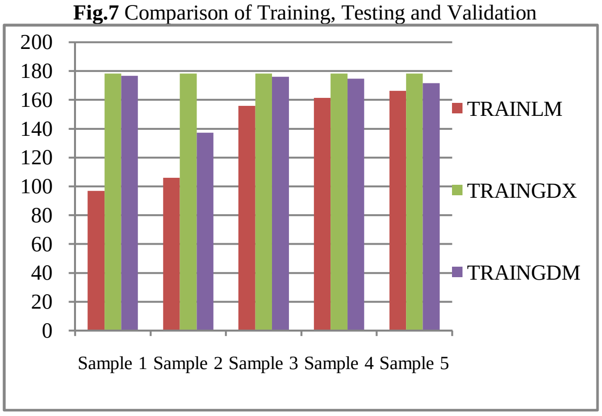


Fig.8 Comparison of Actual Compressive Strength with different Network Architecture

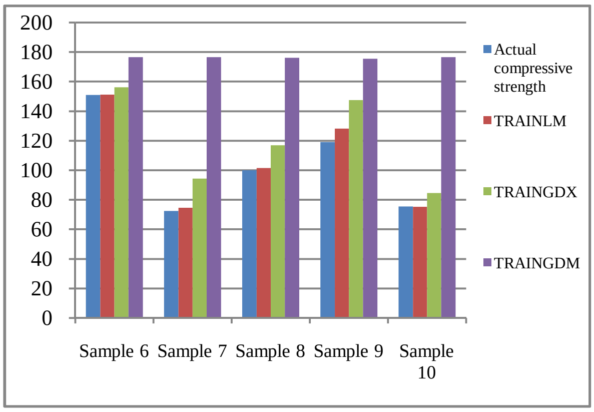


Fig.9 Comparison of Actual Compressive Strength with different Network Architecture

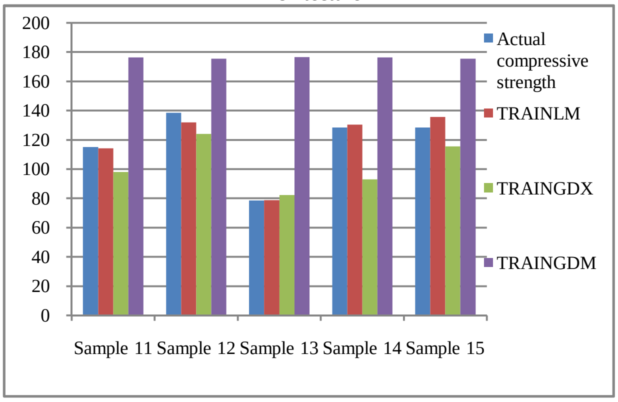


Fig.10 Comparison of Actual Compressive Strength with different Network Architecture

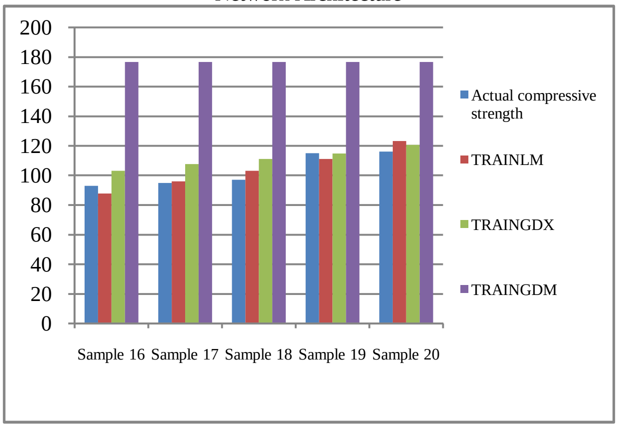


Fig.11 Comparison of Actual Compressive Strength with different Network Architecture

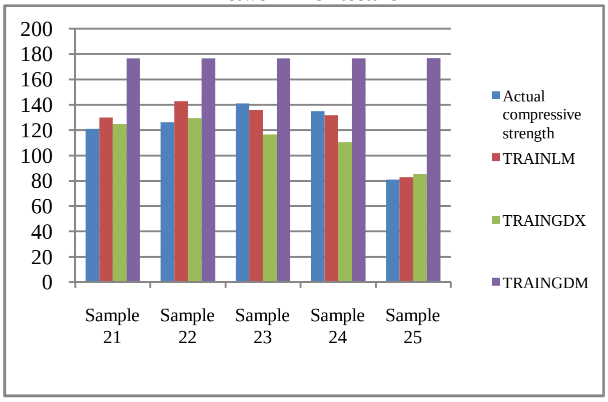


Fig.12 Comparison of Actual Compressive Strength with different Network Architecture

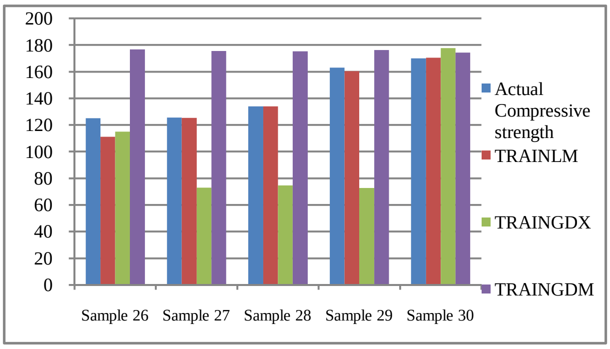


Fig.13 Comparison of Actual Compressive Strength with different Network Architecture

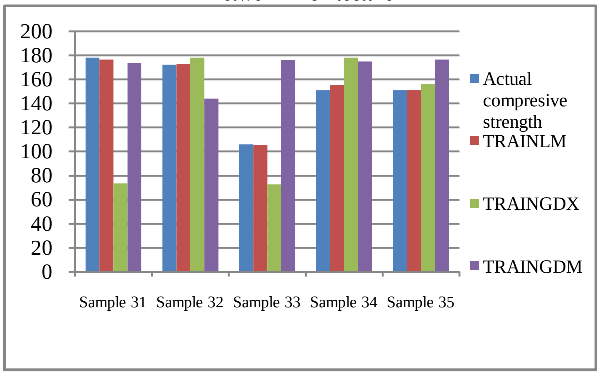


Fig.14 Comparison of Actual Compressive Strength with different Network Architecture

The data are trained with different network architecture and compared with actual compressive strength and the comparison shows that Levenberg-Marquardt network (LM) has given best accuracy result as that of actual compressive strength with minimum error.

CONCLUSION

For development of ANN model for reactive powder concrete mixes with Feed-forward back-propagation training technique has been employed for updating the weights of each layer based on the error in the network output.

It is observed that the predicted values of compressive strength with different network architecture namely LM, GDX, GDM and the values are found to be good when the experiment values are trained with LM value as 3.58. Hence, the developed models are robust and reliable.

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How to cite this article:

Jagannathasn Saravanan and Saranya Poovazhagan., Analitical Study On Compresisve Strength Of Reactive Powder Concrete. *International Journal of Recent Scientific Research Vol. 6, Issue, 5, pp.3872-3880, May, 2015*

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