Modeling of Polymer Modified-Concrete Strength with Artificial Neural Networks

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ABSTRACT: In this paper, artificial neural networks (ANNs) are used in attempt to obtain the strength of polymer-modified concrete (PMC). A database of 36 case records is used to develop and verify the ANN models. Four parameters are considered to have the most significant impact on the magnitude of (PMC) strength and are thus used as the model inputs. These include the Polymer/cement ratio, sand/cement ratio, gravel/cement ratio, and water/ cement ratio. The model output is the strength of (PMC). Multi-layer perceptron trained using the back-propagation algorithm is used. In this work, the feasibility of ANN technique for modeling the concrete strength is investigated. A number of issues in relation to ANN construction such as the effect of ANN geometry and internal parameters on the performance of ANN models are investigated. Design charts for prediction of polymer modified concrete strength are generated based on ANN model. It was found that ANNs have the ability to predict the strength of polymer modified concrete, with a very good degree of accuracy. The ANN models developed to study the impact of the internal network parameters on model performance indicate that ANN performance is reality insensitive to the number of hidden layer nodes, momentum terms or transfer functions. On the other hand, the impact of the learning rate on model predictions is more pronounced.

keywords:; Artificial Neural networks; Strength; Polymer Modified Concrete; Modeling.

الخلاصة

في هذا البحث، جرى استخدام الشبكات العصبية الاصطناعية في محاولة لإيجاد نماذج دقيقة لايجاد مقاومة الخرسانة المطورة بالبوليمر. تم استخدام قاعدة بيانات شملت ما مجموعه 36 لبناء واثبات نماذج الشبكات العصبية الاصطناعية. العوامل الاربعة التالية يمكن اعتبارها من العوامل ذات التأثير الأكبر على مقاومة الخرسانة المطورة بالبوليمر وقد اعتبرت كمعطيات للنموذج وتشمل نسبة البوليمر

الى السمنت، نسبة الرمل الى السمنت، نسبة الحصى الى السمنت،ونسبة الماء الى السمنت ، في حين إن مقاومة الخرسانة هو نتيجة النموذج. في هذا العمل تم استخدام الشبكات المتعددة الطبقات بتقنية الانتشار الرجعي للخطأ لنمذجة مقاومة الخرسانة المطورة بالبوليمر. وقد تمت دراسة العديد من الحالات التي لها علاقة ببناء الشبكات العصبية الاصطناعية منها معمارية الشبكة والعوامل الداخلية لها ومدى تأثيرها على أداء نماذج الشبكات العصبية الاصطناعية، ووضعت اشكال تصميمية لحساب مقاومة الخرسانة المطورة بالبوليمر. لقد وجد بان الشبكات العصبية الاصطناعية لها القابلية على إيجاد مقاومة الخرسانة المطورة بالبوليمر بدرجة جيدة جداً من الدقة. كما أن النماذج التي تم بناءها لدراسة تأثير العوامل الداخلية للشبكات على أداءها أظهرت أن أداء الشبكات غير حساس لعدد العقد في الطبقة المخفية، للحد الكمي و لمعادلات النقل في المقابل فأن تأثير معدل التعلم اكثر وضوحاً على نتائج التوقعات.

1. INTRODUCTION

Most research in material modeling aims to construct mathematical models to describe the relationship between components and material behavior. These models consist of mathematical rules and expressions that capture these varied and complex behaviors. Concrete is a highly nonlinear material, so modeling its behavior is a difficult task. Artificial neural networks are a family of massively parallel architectures that solve difficult problems via the cooperation of highly interconnected but simple computing elements (or artificial neurons). Basically, the processing elements of a neural network are similar to neurons in the brain, which consist of many simple computational elements arranged in layers. Interest in neural networks has expanded rapidly in recent years. Much of the success of neural networks is due to such characteristics as nonlinear processing and parallel processing. In the past decade, considerable attention has been focused on the problem of applying neural networks in diverse fields, such as system modeling, fault diagnosis, and control. This is because neural networks offer the advantages of performance improvement through learning by using parallel processing. The neural network's performance can be measured by the speed of learning (efficiency) and generalization capability (accuracy) of these networks. The speed of learning can be expressed either as CPU time or as the number of epochs required for convergence of the network and thus can form the basis for comparison. There is at present no formal definition of what it means to generalize correctly, but the generalization capability of the network may be assessed based on how well it performs on the test data set. The back-propagation algorithm is now recognized as a powerful tool in many neural-network applications. Most applications of neural networks are based on the back-propagation paradigm, which uses the gradient-descent method to minimize the error function [1,2,3]. In civil engineering, the methodology has been successfully applied to a number of areas. Some typical applications in civil engineering include structural analysis and design [4,5], structural damage assessment [6,7], structural control [8,9], seismic liquefaction prediction [10], constitutive modeling [11,12], compaction characterization [13], geotechnical engineering [14,15,16] and river flow prediction [17].

In the area of material modeling, Ghaboussi et al. [11] modeled the behavior of concrete in the state of plane stress under monotonic biaxial loading and compressive uniaxial cycle loading with a back-propagation neural network. Their results look very promising. Brown et al.[18] demonstrated the applicability of neural networks to composite material characterization. In their approach, a back-propagation neural network had been trained to accurately predict composite thermal and properties when provided with basic information concerning the environment, constituent materials, and component ratios used in the creation of the composite. Kasperkiewicz et al.[19] demonstrated that the fuzzy-ARTMAP neural network can model strength properties of high-performance concrete mixes and optimize the concrete mixes. Yeh[20] demonstrated that a novel neural network architecture, augment-neuron network can improve the performance of these networks for modeling concrete strength significantly. A back-propagation neural network consists of a number of interconnected processing elements (artificial neurons). The elements are logically arranged into two or more layers, and interact with each other via weighted connections. These scalar weights determine the nature and strength of the influence between the interconnected elements. Each element is connected to all the neurons in the next layer. There is an input layer where data are presented to the neural network, and an output layer that holds the response of the network to the input. It is the intermediate layers (hidden layers) that enable these networks to represent the interaction between inputs as well as nonlinear property between inputs and outputs. Traditionally, the learning process is used to determine proper interconnection weights, and the network is trained to make proper associations between the inputs and their corresponding outputs. Once trained, the network provides rapid mapping of a given input into the desired output quantities.

The basic strategy for developing a neural-based model of material behavior is to train a neural network on the results of a series of experiments on material. If the experimental results contain the relevant information about the material behavior, then the trained neural network would contain sufficient information about the material behavior to qualify as a material model. Such a trained neural network not only would be able to reproduce the experimental results it was trained on, but through its generalization capability should be able to approximate the results of other experiments[11].

2. POLYMER MODIFICATION FOR CONCRTE

- **Polymer Portland Cement Concrete (PPCC)**

ACI Manual of Concrete Practice Part 5-1990[21] defines Polymer Portland Cement Concrete (PPCC) mixtures as normal Portland Cement Concrete to which a water soluble or emulsified polymer has been added during the mixing process. As the concrete cures, hardening of polymer also occurs, forming a continuous matrix of polymer throughout the concrete.

n **Polymer Modification for Mortar and Concrete**

The use of polymer modification for cement mortar and concrete is not new. In 1923 using polymers “as an admixture” which consists of polymeric compounds to improve properties such as strength, modulus of elasticity, water proof, durability of cement mortar and concrete was a patent issued to “Cresson”[22], this patent refers to paving material with natural rubber latexes and cement was used as filler.

In Japan, polymer modified mortar is most widely used as a construction material for finishing and repairing works, but polymer modified concrete (PMC) is seldom used because of its poor cost – performance balance, however, the PMC is widely used for bridge deck overlays and patching work in U.S.A; for example 1.2 million m2 of bridge decks are overlaid with polymer modified concrete (PMC) [23] .

In the last decade, about 60300m3 of PMC has been placed each year on both new and existing deteriorated concrete structures in U.S.A.[23] .

To produce polymer-modified mortar and concrete, mostly polymers in dispersion (latex or emulsion) form are added to ordinary cement mortar and concrete during mixing. Polymer-modified mortar and concrete have considerable attraction because their process technology is very similar to that of ordinary cement mortar and concrete. Fig.(1) represents the classification of polymeric admixtures or modifiers for polymer-modified mortar and concrete. The polymer dispersions widely used are styrene-butadiene rubber (SBR) latex, ethylene-vinyl acetate (EVA), and polyacrylic ester (PAE) emulsion in Japan and Europe, and the styrene-butadiene rubber latex, polyacrylic ester emulsion, and epoxy (EP) resin in the United States. Annual consumption of the polymer dispersions in Japan has exceeded 100,000 tons in recent years. In Japan and Europe, the epoxy resin is rarely used as a polymeric admixture because it is more expensive than latex or emulsion polymers. In Europe, Japan, and the United States, redispersible polymer powders are produced by spray-drying polymer dispersions such as ethylene-vinyl acetate and vinyl acetate-vinyl carboxylate emulsions, and often employed for the same purpose as polymer dispersions.

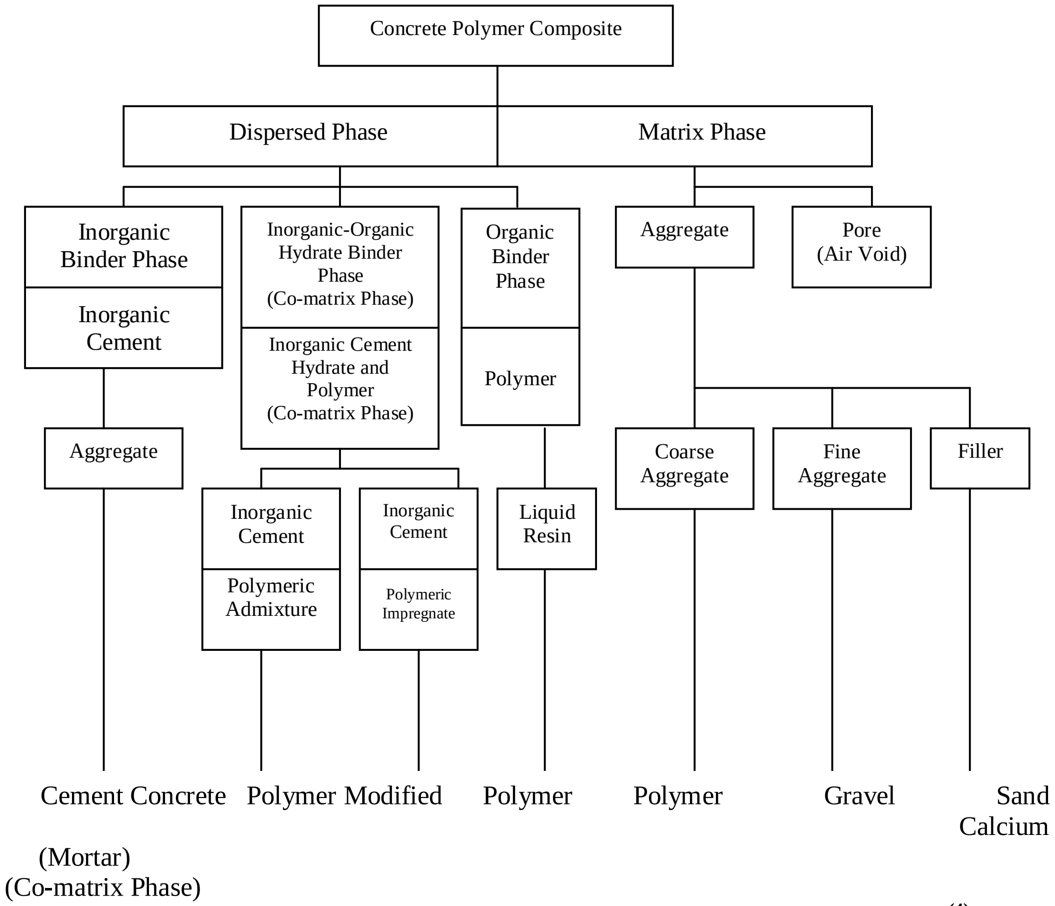
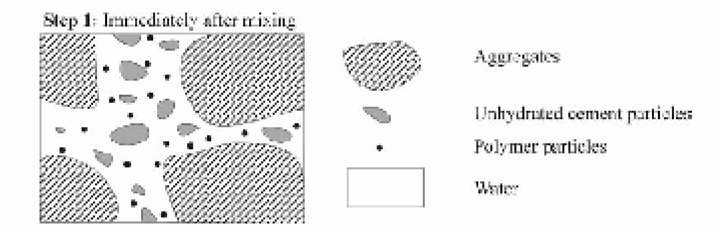


Fig.(1):System and Classification of Concrete-Polymer Composites.[4]

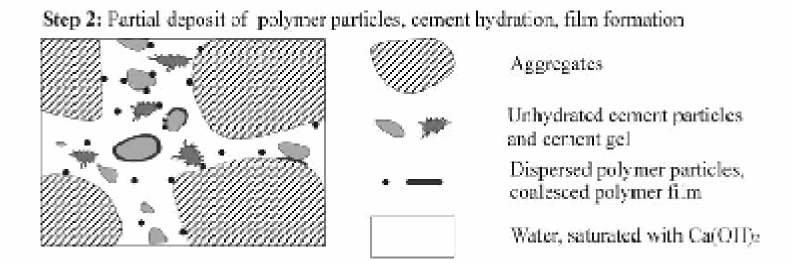
■ Principles of Polymer Modification

Although polymer-based admixtures in any form such as polymer latexes, water-soluble polymers and liquid polymers are used in cementitious composites such are mortar and concrete. It is very important that both cement hydration and polymer film formation (coalescence of polymer particles and the polymerization of resins) proceeds well to yield a monolithic matrix phase with network structure in which the cement hydrate phase and polymer phase interpenetrate. In polymer-modified mortar and concrete structures, aggregates are bound by such co-matrix phase, resulting in superior properties compared with conventional cementitious composite [24].

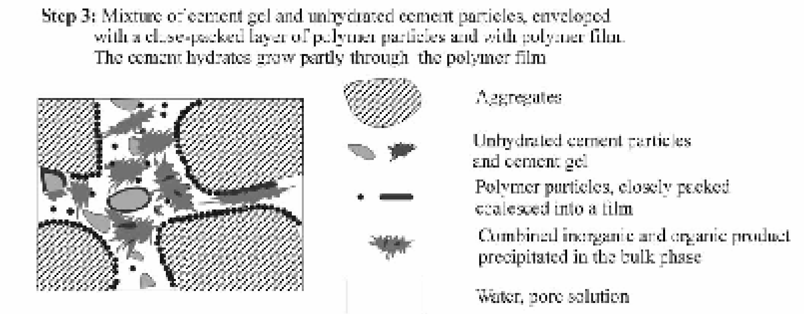
Polymer latex modification of cement mortar and concrete is governed by both cement hydration and polymer film formation. The cement hydration process generally precedes the polymer film formation process by the coalescence of polymer particles in polymer latexes [24,25]. In due course both cement hydration and polymer film formation processes form a co-matrix phase. The co–matrix phase is generally formed according to the simplified model given by Ohama [(24)], and integrated model by Beeldens, et al. [(25)] , shown in fig (2). Some chemical reactions happen between polymer and cement hydration that lead to improve the bond between cement hydrates and aggregates [(24)].



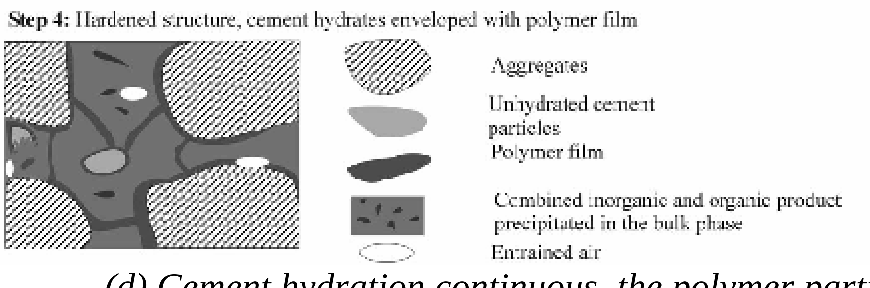
(a) Immediately after mixing



(b) Partial deposit of polymer particles, cement hydration, film formation



(c) Cement hydration proceeds, polymer film formation starts on specific spots



(d) Cement hydration continuous, the polymer particles coalesce into a continuous film

Fig.(2): Integrated model of structure formation [(25)].

■ <u>Styrene Butadiene Rubber (SBR) Polymer Modified Concrete</u>

SBR Polymer is the most widely used in concrete. Fig. (3), shows the chemical structure of Styrene butadiene Rubber latexes.Co-polymers of butidine with styrene (styrene-butadine rubber (SBR)), are a group of large-volume synthetic rubbers[26]. High adhesion occurs between the polymer films that form and cement hydrates. This action gives less strain compared to ordinary concrete and improves the properties of concrete such as flexural and compressive strength and gives also a higher durability [23] .

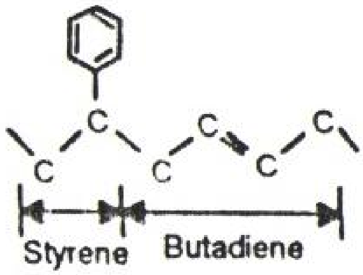


Fig.(3) Chemical structures of SBR polymer latexes [26]

Qusay Abdulhameed Jabal Al-Atiyah[27] added styrene butadiene rubber (SBR) polymer as a ratio of cement content to no-fines concrete in his research to study the effect of SBR polymer on stress-strain relationship of no-fines concrete under compression . That research also includes studying the effect of polymer/cement (P/C) ratio on properties like density, compressive strength and modulus of elasticity.

The concrete mixes by weight were (1:7), (1:6), (1:5), and (1:4) cement/aggregate (C/A). The polymer was added as percentages of cement weight and the ratios of the polymer were (5%), (7.5%), and (10%). Reference mixes of (0%) polymer were made for every case.

Styrene Butadiene Rubber ((SBR) polymer) improved the compressive strength and made this type of concrete (no-fines concrete) less strained than that in reference mixes. It increased the compressive strength in mixes such as (1:4) C/A mixes from (23.6) MPa to (34.1) MPa when P/C ratio increased from (0%) to (10%), with percentage of increase of (44%).

The area under stress-strain curves was found in polymer concrete mixes to be greater than reference mixes and also the area under curves was increased with P/C ratios. Also, the increase in the modulus of elasticity for air-curing was about 61% for (1:7) C/A mixes and 4% for (1:4) mixes when P/C changes from 0% to 10%.

The suitability of no-fines concrete to be used in structural members has been affirmed in that research especially for (1:4), and (1:5) C/A polymer mixes.

A new mathematical model suggested for both ascending and descending portions is presented in that research and discussed.

Several investigators [28,29] studied the influence of the ratio of polymer/cement (P/C). J. . Sauer, and Cook [30], studied the effect of (P/C) ratio on compressive and tensile strength of polymer cement concrete. It should be noted also that in all cases, polymer content greater than 18% does not give additional increase in compressive strength, flexural strength and also modulus of rupture (M.O.R)[31,32].

3. DEVLOPMENT of Neural Network Model

The steps for developing ANN models, as outlined by Maier and Dandy [33], are used as a guide in this work. These include the determination of model inputs and outputs, division and preprocessing of the available data, the determination of appropriate network architecture, optimization of the connection weights training, stopping criteria, and model validation. The personal computer-based software *NEUFRAME* Version 4.0 2000 Neurosciences Corp., Southampton, Hampshire, U.K. is used to simulate ANN operation in this work. The data used to calibrate and validate the neural network model were obtained from the literature and include experimental measurements of concrete strength as well as the corresponding information regarding the mixtures. The data cover a range of variation in polymer cement ratio, sand/cement ratio, gravel/cement ration and water/cement ratio. The database comprises a total of 36 individual cases; 8 cases were reported by Al-Hadithi[34] 8 cases by Al-Kubaisy[35] 4 cases by Al-Omer[36] 6 cases by Al-Hadithi[37] 6 cases by Bentur[32] and 4 cases by Al-Gassani[38].

- **Model Inputs and Outputs**

A thorough understanding of the factors affecting strength of polymer modified-concrete is needed in order to obtain accurate strength prediction. Most traditional works include, as the main factors affecting modified – concert strength, (Polymer/cement ratio, fine aggregate (sand/cement ratio), coarse aggregate (gravel/cement ratio), water/cement ratio, quantity of water, maximum grain size, and age of testing). There are insufficient data for the maximum grain size and quantity of water added while the age of testing is 28 days, and thus these data are not included in the input data. Consequently, four parameters are considered to have the most significant impact on the magnitude of (PMC) strength and are thus used as the model inputs. These include the Polymer/cement ratio (P/C), sand/cement ratio (S/C), gravel/cement ratio (G/C), and water/ cement ratio (W/C), concrete strength is the output. The data ranges used for the ANN model are given in Table (1).

Table(1) Data ranges used for ANN model variables

Model variables	Minimum value	Maximum value
Polymer/cement ratio, (P/C %)	0	30%
Sand/Cement ratio, (S/C)	1.19	2.5
Gravel/Cement ratio, (G/C)	0	4.1
Water/Cement ratio, (W/C)	0.2	0.6
Compressive Strength, (Fc) MPa	9.6	69.6

■ Data Division and Preprocessing

It is common practice to divide the available data into two subsets; a training set, to construct the neural network model, and an independent validation set to estimate model performance in the deployed environment(39). However, dividing the data into only two subsets may lead to model overfitting. As a result, and as discussed later, crossvalidation (40) is used as the stopping criterion in this study and, consequently, the database is divided into three sets: training, testing, and validation. Recent studies have found that the way the data are divided can have a significant impact on the results obtained (41). Shahin et. al.(42) investigated four data division methods, they are random data division, data division to ensure statistical consistency of the subsets needed for ANN model development, data division using self-organizing maps (SOMs) and a new data division method using fuzzy clustering. The results indicate that the statistical properties of the data in the training, testing, and validation sets need to be taken into account to ensure that optimal model performance is achieved. It is also apparent from the results that SOM and fuzzy clustering methods are suitable approaches for data division. Consequently, the database is divided into three sets: training, testing, and validation using SOM technique, in which the inputs Polymer/cement ratio (P/C), sand/cement ratio (S/C), gravel/cement ratio (G/C), and water/ cement ratio (W/C),and corresponding output concrete strength (Fc) of the predictive model are presented to the SOM as inputs. There is no precise rule for determining the optimum size of the map. Consequently, a number of map size are investigated, including 3x3, 4x4, 5x5, 6x6. for all map sizes, the default parameters (e.g., learning rate and neighborhood size) suggested in the software package are used, and training is continued for 10,000 iterations. A grid size of 5x5 is chosen, as it ensures that the maximum number of clusters are found from the training data (43). It is essential that the data used for training, testing, and validation represent the same population (44). Table (2) shows the statistical parameters for the input and output of the artificial neural network model.

Table (2) Input and output statistics for the ANN model

Data set	Statistical parameters	Input Variables				Output
		P/C %	(S/C)	(G/C)	W/C	Fc, MPa
Training n = 17	maximum	30	2.5	4.1	0.6	68.53
	minimum	0	1.19	0	0.2	10.3
	mean	5.06	1.67	2.25	0.37	40.75
	Std.dv.	7.55	0.47	1.33	0.10	18.08
	range	30	1.31	4.1	0.4	58.23
Testing n = 12	maximum	24	2.5	4.1	0.6	65.15
	minimum	0	1.2	0	0.3	9.6
	mean	4.67	1.71	2.47	0.39	37.76
	Std.dv.	6.33	0.47	1.43	0.09	19.71
	range	24	1.3	4.1	0.3	55.55
Validation n = 7	maximum	18	2.5	4.1	0.54	69.6
	minimum	0	1.2	0	0.3	29
	mean	6.43	1.56	2.39	0.40	46.77
	Std.dv.	5.65	0.43	1.41	0.10	16.10
	range	18	1.3	4.1	0.24	40.6

To examine how representative the training, testing and validation sets are with respect to each other t-test and F-test are carried out. The t-test examines the null hypothesis of no difference in the means of two data sets and the F-test examines the null hypothesis of no difference in the variances of the two sets. For a given level of significance, test statistics can be calculated to test the null hypotheses for the t-test and F-test respectively. Traditionally, a level of significance equal to 0.05 is selected. Consequently, this level of significance is used in this research. This means that there is a confidence level of 95% that the training, testing and validation sets are statistically consistent. The results of the t-test and F-tests are given in Table (3).These results indicate that training, testing and validation sets are generally representative of a single population.

Table (3) Null hypothesis tests for the ANN input and output variables

Variable And Data sets	t-value	Lower critical value	Upper critical value	t-test	F-value	Lower critical value	Upper critical value	F-test
Polymer/cement ratio, (P/C %)								
Testing	0.43	-2.05	2.05	Accept	1.42	0.34	3.30	Accept
Validation	-1.38	-2.07	2.07	Accept	1.79	0.30	5.24	Accept
Sand/Cement ratio, (S/C)								
Testing	-0.66	-2.05	2.05	Accept	1.02	0.34	3.30	Accept
Validation	1.69	-2.07	2.07	Accept	1.23	0.30	5.24	Accept
Gravel/Cement ratio, (G/C)								
Testing	-1.29	-2.05	2.05	Accept	0.87	0.34	3.30	Accept
Validation	-0.77	-2.07	2.07	Accept	0.89	0.30	5.24	Accept
Water/Cement ratio, (W/C)								
Testing	-1.55	-2.05	2.05	Accept	1.11	0.34	3.30	Accept
Validation	-2.05	-2.07	2.07	Accept	0.92	0.30	5.24	Accept
Compressive Strength, (Fc) MPa								
Testing	1.26	-2.05	2.05	Accept	0.84	0.34	3.30	Accept
Validation	-2.45	-2.07	2.07	Reject	1.26	0.30	5.24	Accept

Once the available data have been divided into their subsets, it is important to preprocess the data to a suitable form before they are applied to the ANN. Preprocessing the data by scaling them is important to ensure that all variables receive equal attentions during training. In this work, the input and output variables are scaled between 0 and 1.0, using the following equation:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{...(1)}$$

■ Model Architecture

Determining the network architecture is one of the most important and difficult tasks in the development of ANN models. It requires the selection of the number of hidden layers and the number of nodes in each of these. It has been shown that a network with one hidden layer can approximate any continuous function, provided that sufficient connection weights are used [(45)]. Consequently, one hidden layer is used in this study. The number of nodes in the input and output layers are restricted by the number of model inputs and outputs. The input layer of the ANN model developed in this work has four nodes, one for each of the model inputs [i.e., Polymer/cement ratio (P/C), sand/cement ratio (S/C), gravel/cement ratio (G/C), and water/ cement ratio (W/C)]. The output layer has only one node representing the measured value of concrete strength (Fc). In order to obtain the optimum number of hidden layer nodes, it is important to strike a balance between having sufficient free parameters (weights) to enable representation of the function to be approximated, and not having too many so as to avoid over-training and to ensure that the relationship determined by the ANN can be interpreted in a physical sense. Overtraining is not an issue in this study, as crossvalidation is used as the stopping criterion. However, as just discussed, physical interpretation of the connection weights is important, and hence the smallest network that is able to map the desired relationship should be used. In order to determine the optimum network geometry, ANNs with one, two, three, four, five, six, seven, eight and nine hidden layer nodes are trained. It should be noted that 9 is the upper limit for the number of hidden layer nodes needed to map any continuous function for a network with four inputs, as discussed by Caudill [(46)].

■ Weight Optimization (Training)

The process of optimizing the connection weights is known as ‘‘training’’ or ‘‘learning.’’. This is equivalent to the parameter estimation phase in conventional statistical models. The aim is to find a global solution to what is typically a highly nonlinear optimization problem. A feed-forward networks are used. The method most commonly used for finding the optimum weight combination for feed-forward neural networks is the back-propagation algorithm [(1)], which is based on first-order gradient descent. Details of the back-propagation algorithm are beyond the scope of this paper and can be found in many publications e.g. [(47)]. In this study, the general strategy adopted for finding the optimal parameters that control the training process is as follows.

For each trial number of hidden layer nodes, random initial weights and biases are generated. The neural network is then trained with different combinations of momentum terms and learning rates in an attempt to identify the ANN model that performs best on the testing data. The momentum terms used in this study are 0.005, 0.01, 0.05, 0.1, 0.2, 0.4, 0.6, 0.8, 0.95 and 0.99, whereas the learning rates used are 0.05, 0.1, 0.15, 0.2, 0.4, 0.6, 0.8, 0.9 and 0.95. Since the back-propagation training algorithm uses a first-order gradient descent technique to adjust the connection weights, it may get trapped in a local minimum if the initial starting point in weight space is unfavorable. Consequently, the model that has the optimum momentum term and learning rate is retrained a number of times with different initial weights and biases until no further improvement occurs.

■ Stopping Criteria

Stopping criteria are those used to decide when to stop the training process. They determine whether the model has been optimally or sub-optimally trained. As described earlier, the crossvalidation technique [(40)] is used in this work as the stopping criterion, as it is considered to be the most valuable tool to ensure that overfitting does not occur [(48)]. The training set is used to adjust the connection weights. The testing set measures the ability of the model to generalize, and the performance of the model using this set is checked at many stages of the training process, and training is stopped when the error of the testing set starts to increase. The testing set is also used to determine the optimum number of hidden layer nodes and the optimum internal parameters (learning rate, momentum, and initial weights).

■ Model Validation

Once the training phase of the model has been successfully accomplished, the performance of the trained model is validated using the validation data, which have not been used as part of the model building process. The purpose of the model validation phase is to ensure that the model has the ability to generalize within the limits set by the training data, rather than simply having memorized the input–output relationships that are contained in the training data. The coefficient of correlation (r), the root-mean-square error RMSE), and the mean absolute error (MAE) are the main criteria that are used to evaluate the performance of the ANN models developed in this work. The coefficient of correlation is a measure that is used to determine the relative correlation and the goodness-of-fit between the predicted and observed data. The RMSE is the most popular measure of error and has the advantage that large errors receive greater attention than smaller ones [(49)]. In contrast, the MAE eliminates the emphasis given to large errors. Both RMSE and MAE are desirable when the data evaluated are smooth or continuous [(39)].

4. Results and Discussion

The impact of the number of hidden nodes on ANN performance is shown in Fig. 4. it can be seen that the number of hidden layer nodes has little impact on the predictive ability of the ANN. Fig. 1 shows that the network with two hidden layer nodes has the lowest prediction error.

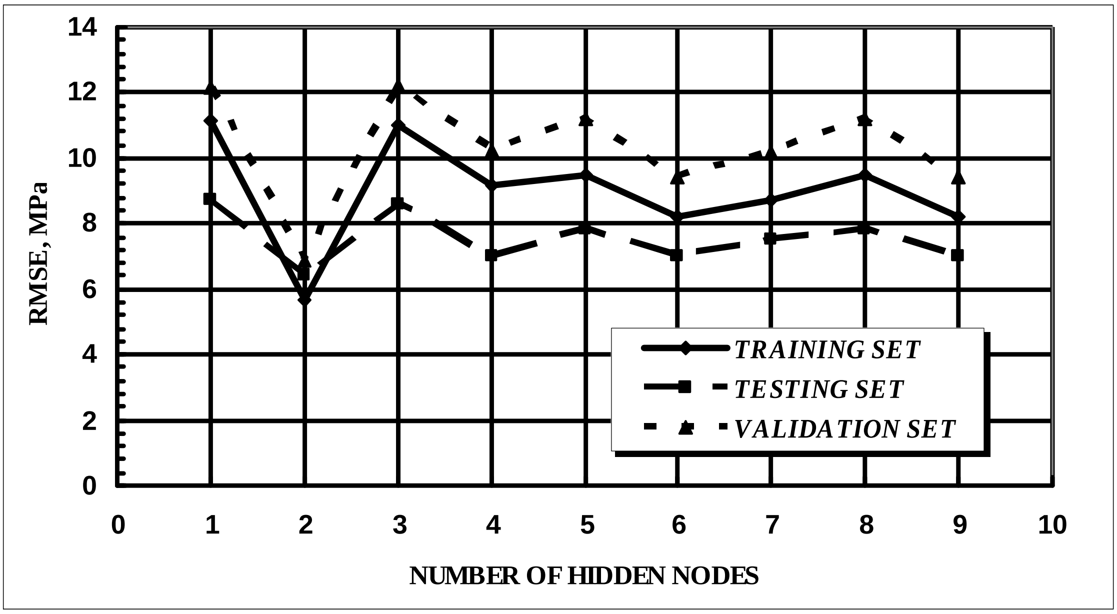


Fig. 4. Performance of artificial neural network models with different hidden layer nodes (learning rate=0.2 and momentum term=0.8)

The effect of the internal parameters controlling the back-propagation algorithm (i.e., momentum term and learning rate) on model performance is shown in Figs. 5 and 6, respectively. It can be seen from Fig. 5 that the performance of the ANN model is relatively insensitive to momentum, particularly in the range 0.01–0.6. The best prediction was obtained with a momentum value of 0.8. Fig. 6 shows that the optimum learning rate was found to be 0.2.

The predictive performance of the optimal neural network model (i.e., two hidden layer nodes, momentum value of 0.8, and learning rate of 0.2) is summarized in Table 4. The results indicate that the ANN model performs well, with an *r* of 0.81, an RMSE of 6.87 Mpa, and an MSE of 6.13 MPafor the validation set. Table 4 also shows that the results obtained for the model during validation are generally consistent with those obtained during training and testing, indicating that the model is able to generalize within the range of the data used for training. The effect of using different transfer functions is shown in Table 5. It can be seen that the better performance is obtained when the tanh transfer function is used for the hidden layer and the sigmoid transfer function is used for the output layer.

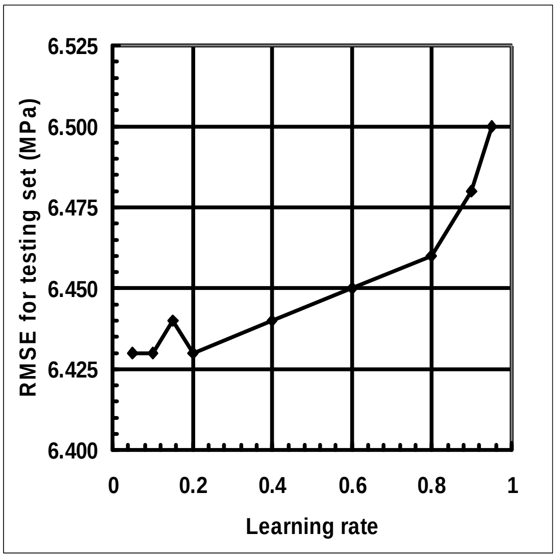


Fig.5 Effect of various momentum terms on artificial neural network performance (hidden nodes = two and learning rate = 0.2)

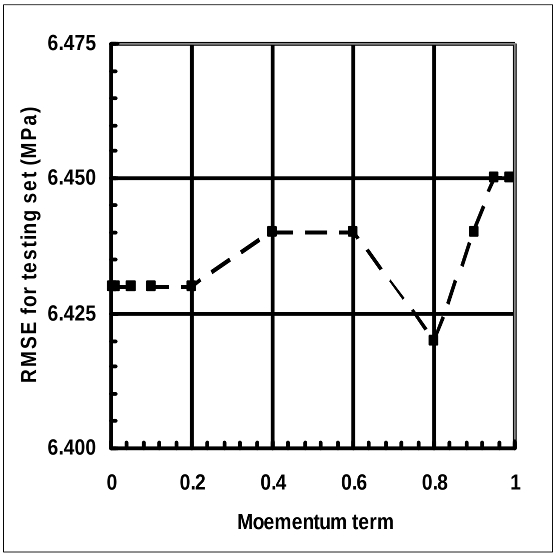


Fig. 6 Effect of various learning rates on artificial neural network performance (hidden nodes = two and momentum term = 0.8)

Table (4) Artificial Neural Network Results

Data set	r	RMSE (MPa)	MAE (MPa)
Training	*0.89*	*5.65*	*4.30*
Testing	*0.87*	*6.43*	*4.43*
Validation	*0.81*	*6.87*	*6.13*

TABLE (5) PERFORMANCE OF ANN MODELS DEVELOPED (NO. OF HIDDEN NODES = 2, LEARNING RATE = 0.2, MOMENTUM TERM = 0.8)

Transfer function in hidden layer	**Transfer function in output layer**	Performance measures								
		Correlation coefficient, r			**RMSE (MPa)**			**MAE (MPa)**		
		T	**S**	**V**	**T**	**S**	**V**	**T**	**S**	**V**
Tanh	**Sigmoid**	***0.89***	***0.87***	***0.81***	***5.65***	***6.43***	***6.87***	***4.30***	***4.43***	***6.13***
Sigmoid	**Sigmoid**	***0.80***	***0.86***	***0.69***	***39.99***	***39.81***	***45.52***	***35.07***	***35.14***	***44.11***
Tanh	**Tanh**	***0.47***	***0.40***	***0.39***	***39.65***	***43.48***	***33.73***	***34.77***	***39.21***	***30.26***

Sigmoid	**Tanh**	***0.80***	***0.86***	***0.69***	***110.78***	***112.25***	***120.58***	***106.17***	***110.65***	***119.66***

T = Training, S = Testing, and V = Validation

Comparisons of the results obtained using the ANN and the measured values of compressive strength are presented in Fig. 7, which shows that the ANN model performs reasonably for all data used in this work.

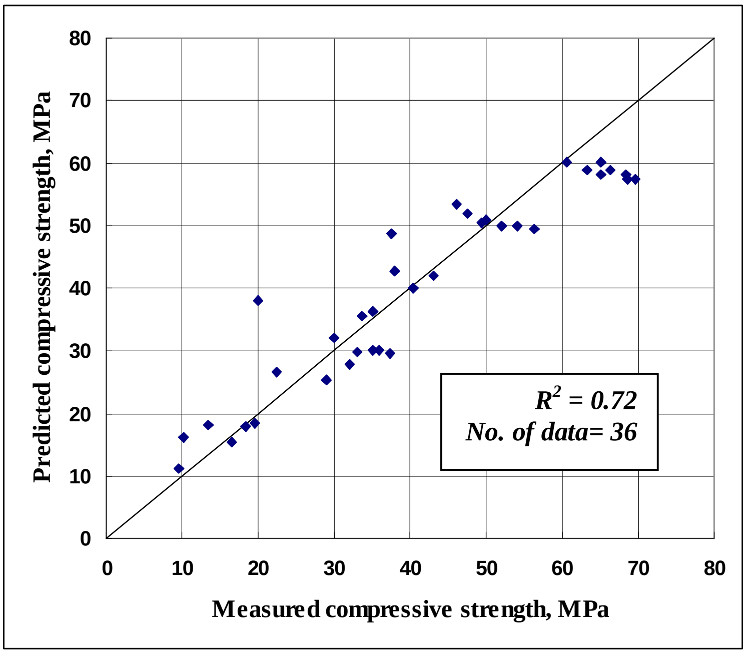


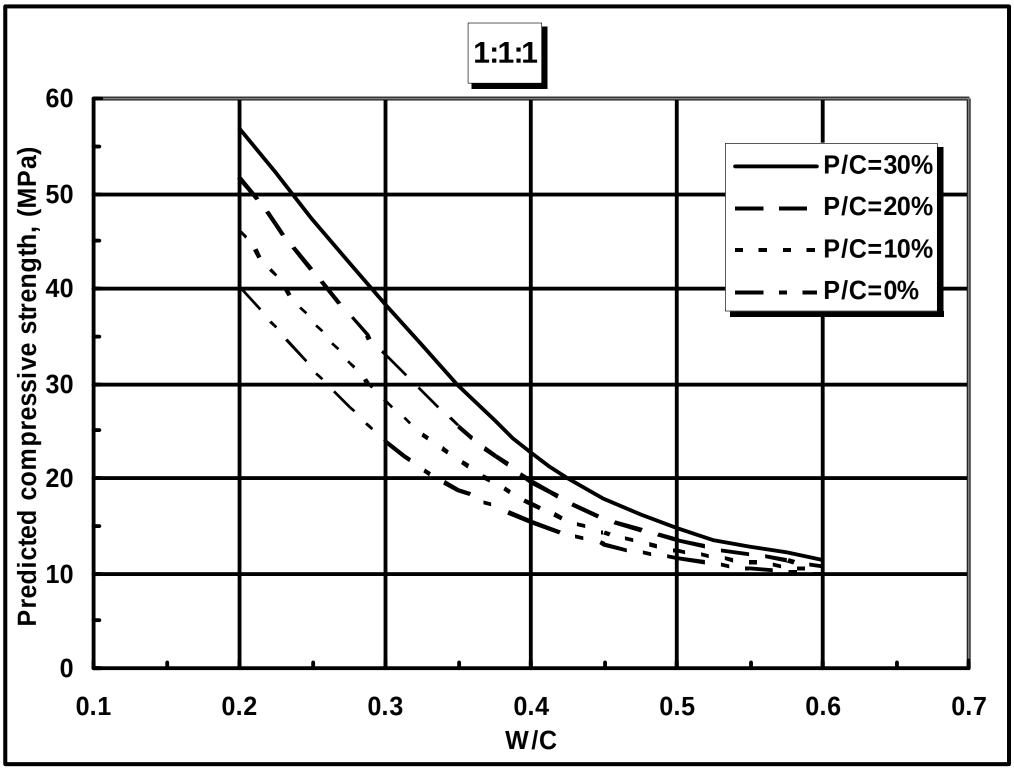
Fig. 7 Measured versus predicted compressive strength for ANN model

In order to facilitate the ANN technique for compressive strength prediction of polymer modified – concrete , the information obtained from the ANN model is translated into a set of design charts suitable for practical use in order to avoid computer or hard calculations. This is carried out by entering synthetic data into the trained ANN model such that the synthetic data lie within the ranges of the data used during the ANN model development. A series of design charts are generated and are shown in Figure 8.

5. CONCLUSIONS

Concrete is a highly nonlinear material, so modeling its behavior is a difficult task. An artificial neural network is a good tool to model nonlinear systems. The results indicate that back – propagation neural networks have the ability to predict the compressive strength of polymer modified concrete with an acceptable degree of accuracy. The predictions obtained using the ANN model were relatively insensitive to the number of hidden layer nodes and the momentum term. The impact of learning rate on model predictions was more pronounced. The optimum network geometry was found to be 4-2-1 (i.e. four inputs, two hidden layer nodes, and one output node), optimum momentum term value was found to be 0.8, and the optimum learning rate was found to be 0.2.

ANNs have the advantage that once the model is trained, it can be used as an accurate and quick tool for estimating the compressive strength without a need to perform any manual work.



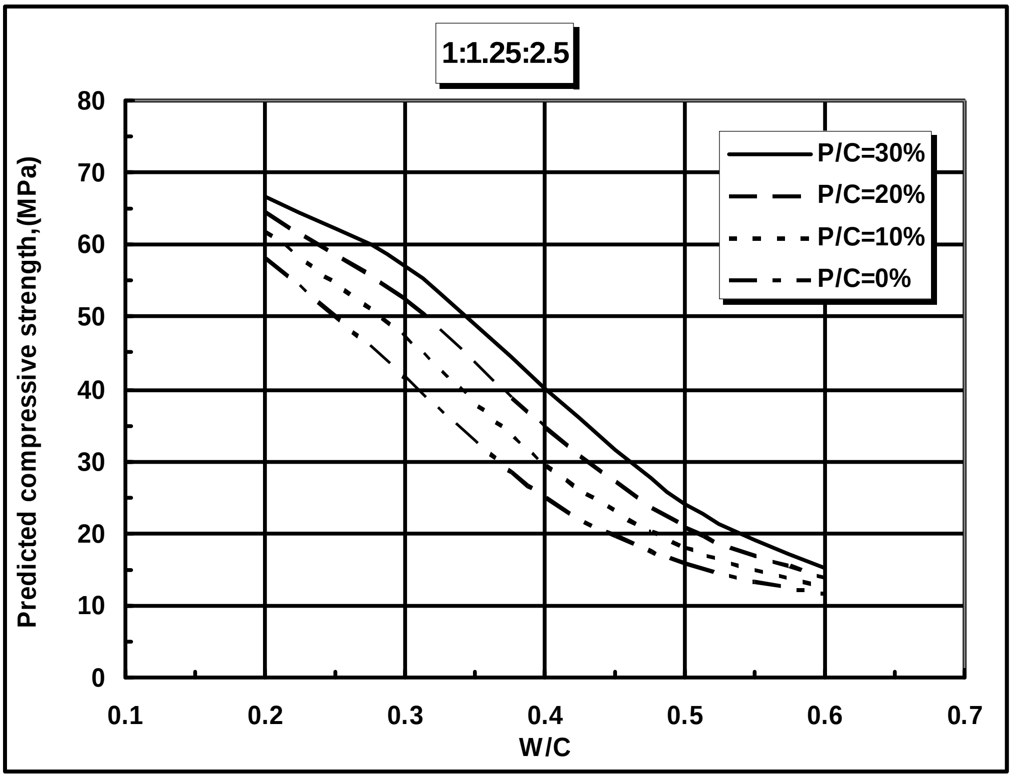
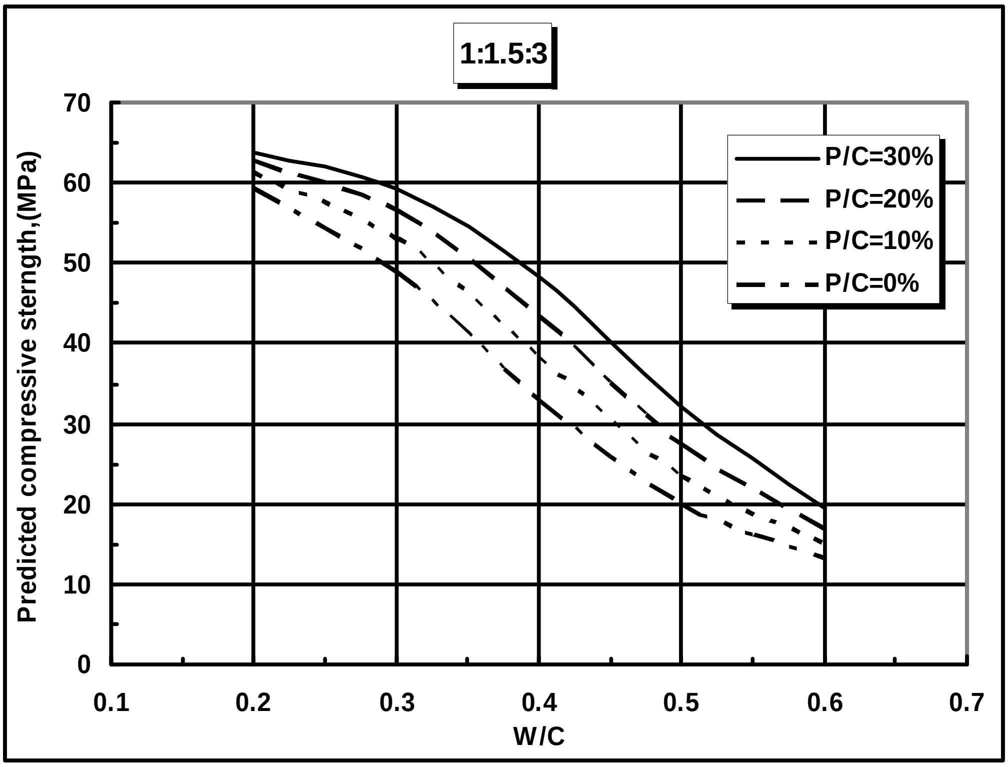


Fig.8 Illustrative set of design charts based on the ANN model



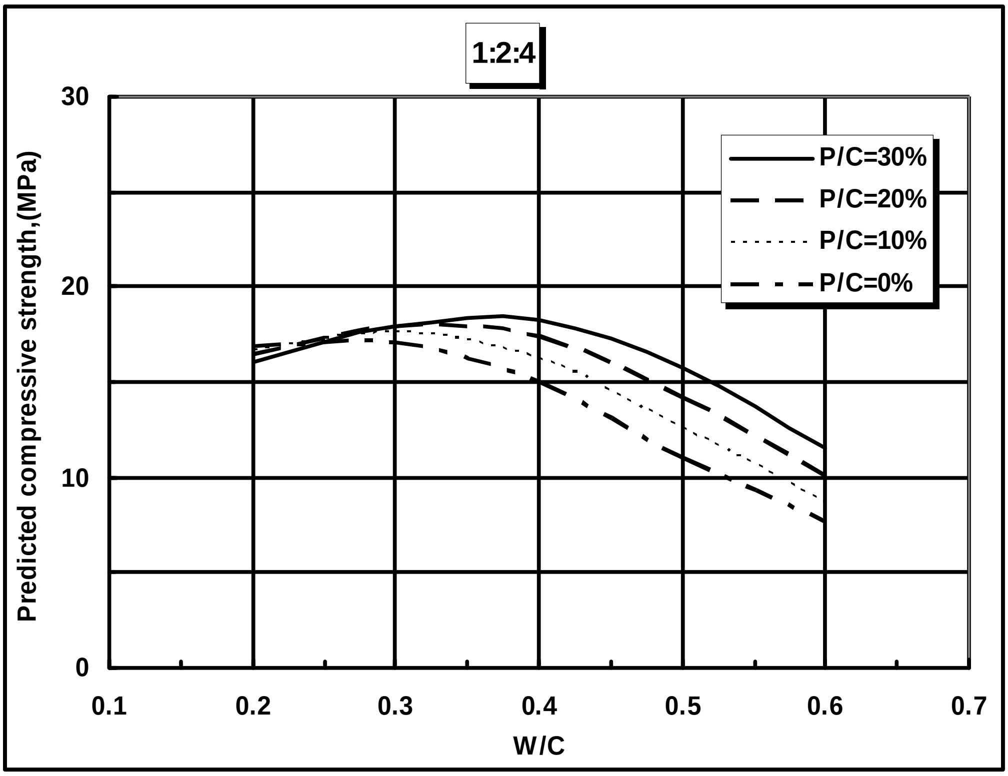


Fig.8 Illustrative set of design charts based on the ANN model (continued)

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