DEVELOPMENT OF GENETIC ALGORITHM BASED HYBRID NEURAL NETWORK MODEL FOR PREDICTING THE ULTIMATE FLEXURAL STRENGTH OF FERROCEMENT ELEMENTS

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Abstract

This paper demonstrates the applicability of Hybrid Neural Networks that combine simple back propagation networks (BPN) and Genetic Algorithms (GAs) for predicting the ultimate flexural strength of ferrocement elements. A hybrid neural network model has been developed to predict the ultimate flexural strength of ferrocement elements with span to depth ratios (3, 6, 9 & 11.45), number of mesh layers (0, 1, 3 & 5) and percentage replacement of silicafume (0, 5, 10, 15, 20 & 25) as input parameters. The network has been trained with experimental data obtained from experimental work. The hybrid neural network model learned the relationship for predicting the ultimate flexural strength in just 300 training epochs. After successful learning, the model predicted the ultimate flexural strength satisfying all the constraints with an accuracy of 95%. The

various stages involved in the development of genetic algorithm based neural network model are addressed at length in this paper.

1. Introduction

Pierre Luigi Nervi conducted the first experimentation on ferrocement. Nervi established the properties of ferrocement as a construction material. From then on many researchers have undertaken and established the mechanical properties of ferrocement [Paul and Pama, 1978]. "Ferrocement is defined as a thin composite made with a cement based mortar matrix reinforced with closely spaced layers of continuous and relatively small diameter wire meshes to create a stiff structural form [Naaman, 2000]. The basic idea behind this material is that the mortar can undergo large strains in the vicinity of reinforcement and the magnitude of strains depends on the distribution of reinforcement throughout the mass of the mortar. The Ferrocement elements are usually of the order of 20 to 35 mm in thickness and the steel requirement varies between 300-500 kg/cum of mortar. The wire mesh used in the Ferrocement material is usually 0.50 to 1.0 mm in diameter at 5 to 25 mm spacing. A Cement-sand proportion of 1:2 or 1:3 is generally used along with a water-cement ratio of 0.40 to 0.50. The advantageous properties of Ferrocement are high tensile strength, toughness, water tightness, lightness, easy repairability, mouldability to any desired shape, durability, fire resistance, environmentally sound technology etc., cannot be matched by any other thin construction material [Naaman, 2000; Atkinson, et al., 1996]. However the applications of Ferrocement are hampered due to non-availability of mix design procedure or a macro model. Development of such a macro model using analytical approach is difficult because of the complex multi parametric relationship between the constituents of Ferrocement. By now it is established that neural networks and Genetic Algorithms have the ability to map this type of multi parametric interaction.

Artificial Neural Networks are highly non-linear and can capture complex interactions among input/output variables in a system without any prior knowledge about the nature of these interactions. In recent years, ANNs have shown exceptional performance as regression tools, especially when used for pattern recognition and function estimation. The main advantage is that one does not have to explicitly assume a model form which is a prerequisite in the parametric approach. In comparison to parametric methods, in ANNs a relationship of possibly complicated shape between input and output variables is generated by data points themselves. In comparison to parametric methods, ANNs tolerate relatively imprecise or incomplete data, approximate results, and are less vulnerable to outliers. ANNs are highly parallel i.e., their numerous independent operations can be executed simultaneously. Among all kinds of neural network algorithms, error back propagation (BP) network is the most typical delegate. But there are some intrinsic drawbacks for the BP algorithm due to its slow convergence rate and tapping in a local optimization. Furthermore, it needs plenty of training samples in model establishment. Genetic Algorithm (GA), on the other hand is a stochastic global searching and optimization algorithm that based on Darwin's biological theory of evolution and the Mendel's genetic principles of genes. GA is used to solve complicated problems by simulating the evolutionary course of natural selection and natural inheritance of biology circles, featured by many advantages such as simple searching method, strong robustness, global parallel searching, and is suitable to solve the complex problems of large scale. GA optimize the encoding string groups which composed by parameters, according to a certain fitness function and genetic operations (Selection, crossover and mutation) on the individual implementation of the evolution, so that high fitness value individual has been preserved and form a new group. While the individual of new group is evolving, fitness value is increasing continually until the limit meets certain conditions. At this point the highest fitness value of the individual shall be the optimum solution. However, GA also has its own shortages such as lower local convergence speed, inclining to premature convergence etc. According what is mentioned above, it is evident that there is strong complementarity between BP and GA. Based on that complementarity, a new hybrid evolution mode can be established; that is, the relationship model is established by BP network, the connection weights and thresholds of BP are optimized by GA, and then the precision of model is increased by BP. It not only avoids the deficiency of BP and GA, but also gives full play to the global searching capacity of the GA and local searching capacity of BP network. Moreover, it accelerates the convergence speed of the algorithms and overcomes the drawback of BP network that is difficult to achieve a satisfactory model with fewer training samples.

Hence in the present paper a hybrid neural network which combines the features of genetic algorithms and back propagation networks is presented as an improved approach for predicting the ultimate flexural strength of Ferrocement elements.

2. Literature Survey

Eldin et al. [1994] employed a NN for measuring and predicting of strength of rubberized concrete. Employing the ANN method for modeling the strength of high performance concrete was investigated by Yeh [1998]. Wang [1999] developed an automatic knowledge acquisition system based on NNs to design concrete mix. Savic et al. [1999] developed software for the optimal design of general and symmetric/balanced laminates (or sandwich panels) with specified mechanical properties. Guang et al. [2000] proposed a method to predict the compressive strength of concrete using multi layer feed forward NNs. Hayalioglu [2000] presented a genetic algorithm for the optimum design of geometrically non-linear elastic-plastic steel frames with discrete design variables. Saka et al. [2000] developed a genetic algorithm based method for the optimum design of grillage systems. Nehdi et al. [2001] have developed a neural network model for predicting performance of self compacting concrete mixtures using feed forward back propagation algorithm. Nehdi et al. [2001] have developed Neural Network models for performance of cellular concrete mixtures. Diasm et al. [2001] presented an ANN model for predicting the strength and slump of ready mixed concrete. Yang et al. [2002] presented an inverse procedure for the detection of a three dimensional crack in plates and shells using genetic searching algorithm. Cengiz Toklu [2005] formulated an aggregate-blending as a multi-objective optimization problem and solved by using genetic algorithms. Sudarsana Rao and Chandrasekhara Reddy [2008] have developed Artificial Neural Network based macro mechanical model for slurry infiltrated fibrous concrete using multi layer feed forward network with back propagation learning algorithm. However, at present there are no such models available for Ferrocement. This paper presents the methodology to develop a GA based ANN macro model for predicting the flexural strength of Ferrocement elements.

3. Development of hybrid neural network model

Development of a hybrid neural network model for predicting the ultimate flexural strength of ferrocement elements involves various stages which are addressed in the following sections.

3.1 Generation of exemplar patterns

Experiments were conducted to determine the ultimate flexural strength of Ferrocement elements after 28 days of curing with span to depth ratio (3, 6, 9 & 11.45), number of mesh layers (0, 1, 3 & 5) and percentage replacement of silicafume (0, 5, 10, 15, 20 & 25) as variables. A total of 288 Ferrocement elements were cast and tested in the laboratory for flexure and the average of three samples were considered so as to get 96 data sets of results. Out of this 96 data sets, 77 data sets (80% of total data) were used for training and the remaining 19 data sets were used for validation. A part of the training set data is presented in Table No.1.

3.2 Selection of input and output vectors

In the present work, it is required to develop a hybrid network model for predicting the flexural strength of Ferrocement elements. This means, the model should be able to predict the values of ultimate flexural strength for a given input vector of span to depth ratio (a/D), number of mesh layers (N) and percentage of silica fume (%SF). Accordingly the input to the network is selected as follows.

1. Span to depth ratio (a/D)
2. Number of mesh layers (N)
3. Percentage of silica fume (%SF)

The input vector selected for this model is

$$IP = [\ a/D,\ N,\ \%SF]$$

The output of the network is

Ultimate Flexural Strength (UFS)

Accordingly, the output vector for the Neural Network model is selected as

$$OP = (UFS)$$

Table No.1: Part of the training data set

Sl.No.	Input Vector			Output Vector
	Span to Depth ratio (a/D)	Number of Mesh Layers (N)	Percentage of Silica fume (%SF)	Ultimate Flexural Strength (UFS) in N/mm^2
1	3	0	0	3.06
2	3	1	15	3.24
3	3	3	5	4.23
4	3	3	10	4.59
5	3	5	20	4.50
6	6	0	5	3.42
7	6	1	25	2.88
8	6	3	15	4.32
9	6	5	10	5.58
10	6	5	15	5.04
11	9	0	15	3.51
12	9	1	10	4.56
13	9	1	25	2.97
14	9	3	10	5.40
15	9	5	5	5.67
16	11.45	0	0	3.43
17	11.45	1	10	4.80
18	11.45	3	5	5.48
19	11.45	5	15	5.83
20	11.45	5	20	5.14

3.3 Scaling of Data

The input and output parameters have been normalized in the range (0, +1) using suitable normalization factors or scaling factors. The scaling factors for input and output parameters are presented in the Table No.2.

Table No.2: Scaling of Data

Nature of vector	Parameter	Minimum Value	Maximum Value	Scale Factor
Input vector	Span to depth ratio (a/D)	3	11.45	15
	Number of mesh layers (N)	0	5	8
	Percentage of silica fume (% SF)	0	25	40
Output vector	Ultimate Flexural Strength (UFS) N/mm^2	2.25	6.51	10

3.4 Selecting a suitable network configuration

The network configuration is defined in terms of the number, size, nodal properties, etc. of the input/output vectors and the intermediate hidden layers. Once the input and output vectors are decided to cater the present investigation requirements, the task of selecting a suitable configuration has been taken up. There is no direct method to select number of nodes in hidden layer. Generally a trial and error method is adopted for arriving at the network configuration. After doing a few trials, it is observed that the network with 10 neurons in one hidden layer is behaving well. Accordingly a configuration of (3-10-1) has been selected for this network model. The architecture is depicted in Figure No.1.
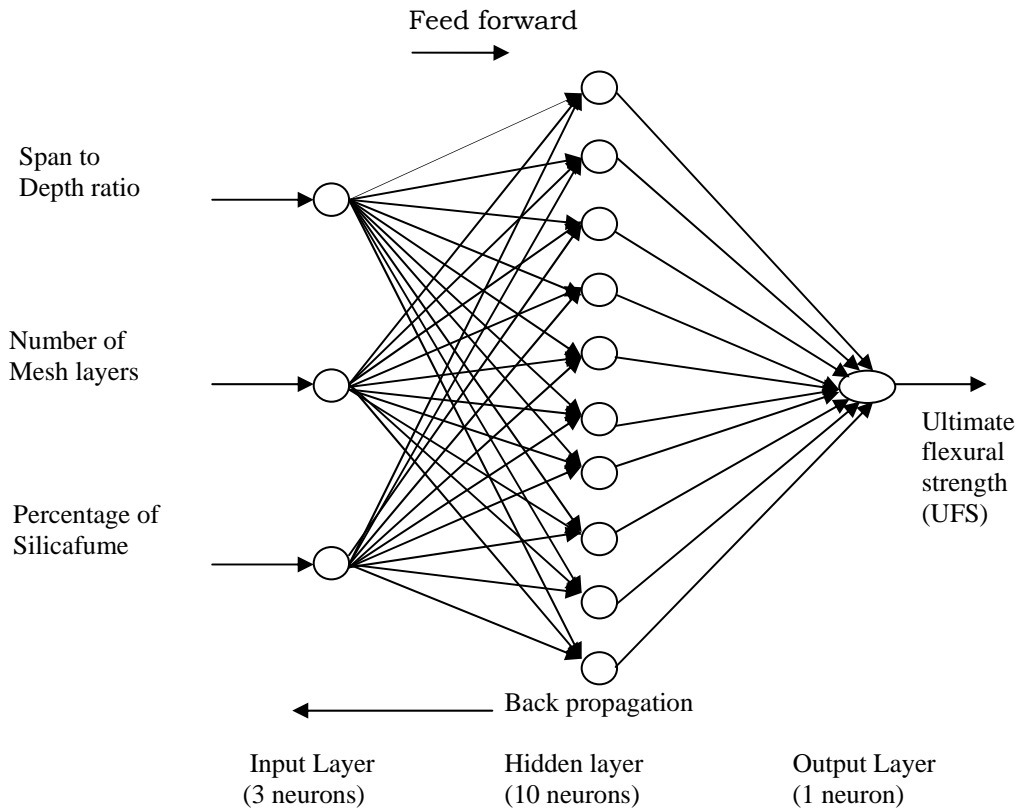
Figure No.1: Configuration of GA/ANN Model

3.5 Training of the network model

Conventionally, a BPN determines its weights based on a gradient search technique and hence runs the risk of encountering local – minima. GA on the other hand is found to be good at finding 'acceptably good' solutions. The idea to hybridize the two networks has been successful to enhance the speed of training [Rajasekaran and Vijayalakshmi Pai, 2003]. In the present work, the weights for the BPN have been obtained by using a GA. Genetic Algorithms (GAs) which use a direct analogy of natural behaviour, work with a population of individual strings, each representing a possible solution to the problem considered. Each individual string is assigned a fitness value which is an assessment of how good a solution is to a problem. The high-fit individuals participate in "reproduction" by cross-breeding with other individuals in the population. This yields new individual strings as offspring which share some features with each parent. The least-fit individuals are kept out from reproduction and so they "die out". A whole new population of possible solutions to the problem is generated by selecting the high-fit individuals from the current generation. This new generation contains characteristics which are better than their ancestors. The parameters which represent a potential solution to the problem, *genes,* are joined together to form a string of values referred to as a *Chromosome*. A decimal coding system has been adopted for coding the *chromosomes* in the present work. The network configuration chosen for the present work is 3-10-1. Therefore, the number of weights (*genes*) that are to be determined are 3x10+10x1=40. With each gene being a real number, and taking the gene length as 5, the string representing the *chromosomes* of weights will have a length of 40x5=200. This string represents the weight matrices of the input-hidden layer-output layers. An initial population of *chromosomes* is randomly generated. Weights from each *chromosome* have been extracted then using the procedure suggested by Rajasekaran & Vijayalakshmi Pai [2003]. The fitness function has been devised using FITGEN algorithm [Rajasekaran & Vijayalakshmi Pai, 2003]. A constant learning rate of 0.6 and a momentum factor of 0.9 have been adopted during the training. Satisfactory training has been obtained after just 300 training cycles. The progress of the learning of the network is presented in Table No.3. It can be seen from Table No.3, that the RMS error after 300 cycles is only 0.0483. Accordingly the performance of the network is acceptable. At this stage the training of the network is terminated to avoid over training. Such an overtraining may hamper the generalization capabilities of the network. The training of the network accepted at this stage is presented in Figure No.2. The figure is drawn only for twenty training examples selected at random. Though the figure is drawn for only twenty examples the author has

verified all the seventy seven training examples and it is found that the network has predicted all the values to the good satisfaction. Thus it can be concluded that at this stage the network has learnt the relationship between input and output parameters successfully.

Table No.3: Learning progress of the network

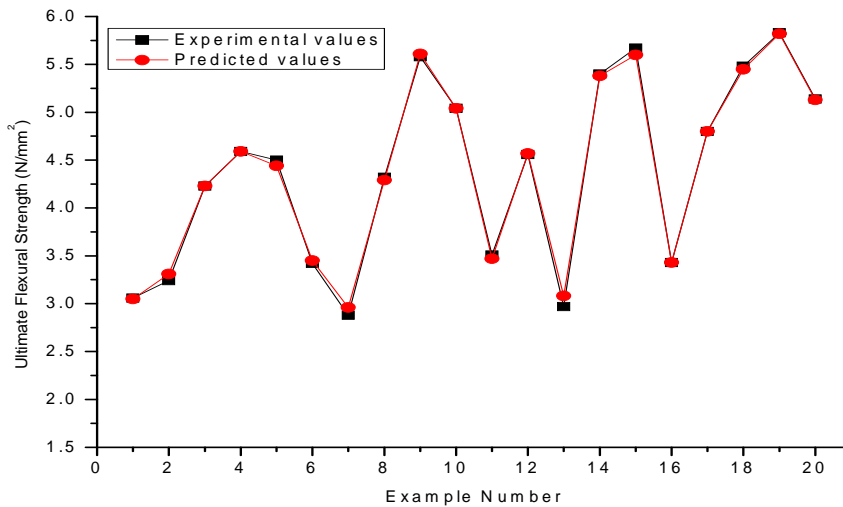| Sl. No.	No. of Epochs	RMS Error
1	100	0.0860
2	200	0.0675
3	300	0.0483

Figure No.2: Learning of GA/ANN Model for Ultimate Flexural Strength

3.6 Validation of the network model

Validation of the network is to test the network for parameters that are not used in the training of the network. The network was asked to predict flexural strength for 19 new data sets which are not included in the training set. It can be observed that from the Figure No.3, the values predicted by hybrid model for new sets matches satisfactorily with the experimental results. Hence, the results of GA based ANN model can be used for prediction of flexural strength of Ferrocement elements.
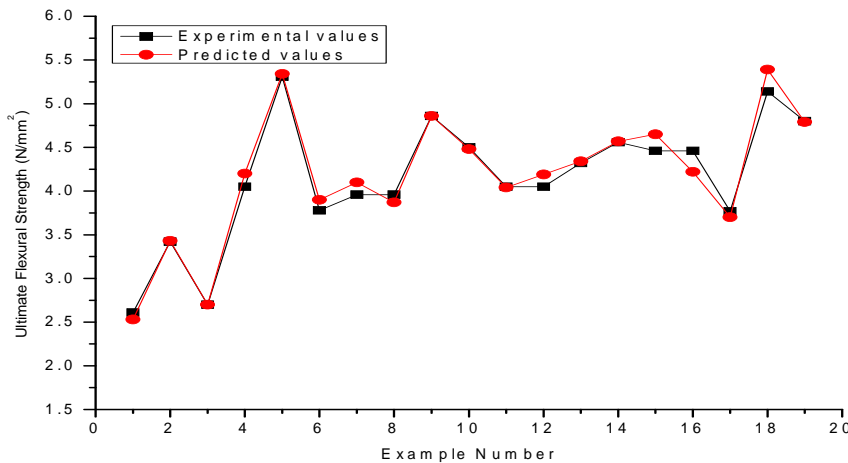

Figure No.3: Validation of GA/ANN model for Ultimate Flexural Strength

4. Conclusions

In this paper, the application of Genetic Algorithm based neural network macro model for predicting the ultimate flexural strength of Ferrocement elements has been demonstrated. The hybrid neural network model has been trained using 77 examples obtained from experimental results. The training examples are so chosen that they will cover all the variables involved in the problem. The weights for the network have been obtained using a genetic algorithm. The network could learn the strength prediction problem with just 300 training cycles. After successful training, the neural network model is able to predict the ultimate flexural strength of ferrocement elements satisfactorily for new problems with an accuracy of about 95%. Thus, it is concluded that the developed hybrid neural network model can serve as a macro-mechanical model for predicting the ultimate flexural strength of ferrocement elements.

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