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# Neural Network (NN) Model to Predict the Flexural Strength of Metakaolin Blended Polypropylene Fiber - Reinforced High-Performance Concrete

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**ABSTRACT**

*The flexural strength of Metakaolin blended Polypropylene Fiber Reinforced High Performance Concrete(MK-PFRHPC) is influenced by various parameters such as water-binder ratio, percentage weight of admixture, percentage weight of fibers, ratio fine aggregate to coarse aggregate and aggregate-binder ratio. Due to nonlinear interaction among these parameters, prediction of flexural strength (F) of such HPC has become an onerous task. However it is overcome by an effective application of machine learning process using NN, a new technology that has emerged from fairly accurate simulation of human brain. In the current research paper, training examples are generated by conducting flexural test in hardened state of concrete at water-binder (W/B) ratios of 0.325, 0.35, 0.375, 0.4, with 0%, 10%, 20%, 30% weight of metakaolin (MK) replacing cement, at 0%, 0.5%, 1.0%, 1.5%, 2.0% polypropylene (PP) fibers replacing cement by weight, for aggregate-binder(A/B) ratios of 2.0 and 2.5. A total of 160 mix samples are prepared and out of which 140 samples are used for training the feed forward neural network model with 4-6-1 architecture (4 input neurons i.e; A/B ,MK,W/B, PPF; 6 neurons in the hidden layer and one output neuron i.e; flexural strength F) and the remaining 20 samples are used for validation of the model. After successful training, it is found that the developed neural network model is able to predict the flexural strength of MK-PFRHPC mixes accurately and efficiently.*

***Key words**: High performance concrete, Metakaolin, Polypropylene fibers, Water-binder ratio, Aggregate-binder ratio, Flexural strength, Neural Network model.*

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## INTRODUCTION

### Applications of ANNs - A critical Review

The first journal article on the applications of neural networks in civil/structural engineering was published in 1989 in Computer-Aided Civil and Infrastructure Engineering. The computational simulation of composite ply micro-mechanics using ANNs was reported by Brown et al. [1].

Kasperkiewicz et al. [2] applied ANNs for predicting strength properties of HPC mixes. Composition of HPC was assumed to simplified, as a mixture of six components (cement, silica, super-plasticizer, water, fine-aggregate and coarse-aggregate) and the results suggested that the problem of concrete strength prediction can be effectively modeled into a neural system in spite of data complexity, incompleteness and incoherence and the approach can be used in multi-criteria search for optimal concrete mixes. Hegazy et al. [3] used neural networks as a means to develop efficient predictive models of the structural behavior of concrete slabs. Patodi and Purani [4] used feed forward neural networks to predict the flexural behavior of steel fiber-reinforced concrete beam and the results obtained for both the problems were found to be in good agreement with the actual experimental values. Patodi and Satodia [5] applied back-propagation algorithm to predict the behavior of fiber-reinforced concrete deep beams using a menu driven simulator developed in FORTRAN 90. Hadi Muhammad [6] applied Back-propagation networks using the programming package MAT-LAB andfound that the amount of CPU memory consumed by NNs was less than that consumed by conventional methods and were easy to use and implement. Labossière [7] applied artificial neural networks to predict the failure of anisotropic materials under any loading condition and illustrated the failure envelope for a typical fibre-reinforced material. Sudarsana Rao and Chandrasekhar [8] developed a macro-mechanical network model to predict compressive, tensile and flexural strengths for slurry infiltrated fibrous concrete with four input parameters viz. percentage volume of fibers, aspect-ratio, and admixture type and percentage weight of admixture.

### Back-propagation algorithm

Back-propagation was created by generalizing the Windrow-Hoff learning rule to multi-layer networks and non-linear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors or classify input vectors in an appropriate way as we define. Networks with biases, sigmoid layer and linear output-layer are capable of approximating any function with a finite number of discontinuities. The derivation of back-propagation algorithm can be found elsewhere [9].

Standard back-propagation is gradient-descent algorithm, as is the Windrow-Hoff learning rule in which the network weights are moved along the negative gradient of the performance function. The mathematical basis for the back-propagation algorithm is the optimization technique known as gradient-descent. The gradient of a function (in this case the function is the error and the variables are the weights of the net) gives the direction, in which the function increases more rapidly. The negative of the gradient gives the direction, in which the function decreases more rapidly.

Properly trained back-propagation networks tend to give reasonable answers, when presented with inputs they have never seen. Typically, a new input led to the correct output for input vectors used in training that are similar to the new inputs being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

The feed forward back-propagation network undergoes supervised training, with a finite number of pattern pairs consisting of an input pattern and a desired or target output pattern. The back-propagation training consists of two passes of computation: *a forward pass and backward pass*.

In the forward pass an input pattern is presented at the input-layer. The neurons here pass the pattern activations to the next layer (hidden) neurons. The outputs of the hidden-layer neurons are obtained by using perhaps a bias and also threshold function with the activations determined by the weights and the inputs. These hidden-layer outputs become inputs to the output neurons, which process the inputs using an optional bias and threshold function. The final output of the network is determined by the activations from output-layer.

During the forward pass the synaptic weights of the networks are all fixed and during the backward pass the synaptic weights are all adjusted in accordance with the error correction rule. The computed pattern and the input pattern are compared, a function of this error for each component of the pattern is determined and adjustment to weights of connections between the hidden-layer and the output-layer is computed.

A similar computation, still based on the error in the input, is made for the connection weights between the input and hidden-layers. The procedure is repeated with each pattern pair assigned for training the network. Each pass through all the training patterns is called a cycle or epoch. The process is then repeated as many cycles as needed until the error is within a prescribed tolerance.

## STEPS INVOLVED IN THE DEVELOPMENT OF BACK-PROPAGATION NEURAL NETWORK

a). Generation of exemplar patterns b). Selection of networkc).Selection of Input and output d). Configuration of network e). Training of Network f).Validation of Network

a). Generation of Exemplar Patterns

Out of 160 different sets of mixes of MK-PFRHPC, 140 data sets of mixes are used for training and the remaining 20 data sets of mixes are employed for validation. The experiments are conducted at four different W/B ratios (viz. 0.325, 0.35, 0.375 and 0.40) with four percentage weight of metakaolin (viz. 0, 10, 20 and 30), at five different percentage weight of PP fibers (viz. 0.0, 0.5, 1.0, 1.5 and 2.0) for two different aggregate-binder ratios (viz. 2.0 and 2.5). For each mix, the effects of W/B ratio, percentage weight of metakaolin, percentage weight of PP fibers and the aggregate-binder ratio on flexural strength of the MK-PFRHPC mixes are evaluated.

b). Selection of network

A feed forward neural network that has the potential to map non-linear and complex relations with lot of interdependencies and uncertainty among the input and output parameters is selected.

c). Selection Input and Output

Input: Aggregate-binder ratio (A/B), Percentage PP fibers by weight of cementitious material ($W_f$), Percentage weight of metakaolin replacing cement (MK), Water-binder ratio (W/B).

Output: Flexural strength (F).

Part of input and output data for training is shown in Table – 2.

Since the neural networks can be trained well and faster, if the data values lie in between 0 and +1, i.e. binary, the input and output parameters are scaled to lie in the range [0 +1] using suitable scaling factors.

The scaling factors for the input and output nodes are shown in Table - 1. Since water-binder ratio value lies in between 0 and 1, no scaling factor is used on it.

Table - 1 Scale factors for input and output nodes

| **Input** | | | | |
|---|---|---|---|---|
| Node | Parameter | Maximum value | Minimum value | Scale factor |
| 1 | A/B | 2.5 | 2.0 | 5 |
| 2 | $W_f$ | 2.0 | 0 | 5 |
| 3 | MK | 30 | 0 | 50 |
| 4 | W/B | 0.40 | 0.325 | -- |
| Output | | | | |
| 1 | F | 10.10 | 4.88 | 15 |

**Table - 2 Part of Input and output data for training**

| Mix Id No. | A/B | $W_f$ | MK | W/B | F | |
|---|---|---|---|---|---|---|
| | | | | | Expt | BPN |
| 1 | 2.0 | 0.0 | 0 | 0.325 | 7.56 | 7.5155 |
| 2 | 2.5 | 2.0 | 0 | 0.350 | 5.98 | 5.9194 |
| 3 | 2.0 | 1.0 | 20 | 0.325 | 9.61 | 9.6922 |
| 4 | 2.5 | 0.5 | 0 | 0.400 | 6.33 | 6.3251 |
| 5 | 2.0 | 0.0 | 10 | 0.325 | 8.58 | 8.6196 |
| 6 | 2.5 | 2.0 | 0 | 0.375 | 5.65 | 5.6952 |
| 7 | 2.0 | 0.0 | 20 | 0.350 | 6.43 | 6.4821 |
| 8 | 2.5 | 0.5 | 30 | 0.375 | 6.05 | 6.0872 |
| 9 | 2.0 | 1.5 | 0 | 0.375 | 7.68 | 7.7192 |
| 10 | 2.5 | 0.0 | 10 | 0.400 | 6.45 | 6.3791 |
| 11 | 2.0 | 0.0 | 30 | 0.350 | 5.93 | 5.8849 |
| 12 | 2.5 | 1.0 | 20 | 0.325 | 9.27 | 9.1935 |
| 13 | 2.0 | 1.5 | 10 | 0.400 | 7.55 | 7.5802 |
| 14 | 2.5 | 0.5 | 0 | 0.375 | 6.52 | 6.5746 |
| 15 | 2.0 | 0.5 | 10 | 0.375 | 7.56 | 7.5882 |
| 16 | 2.5 | 2.0 | 20 | 0.325 | 6.94 | 7.0226 |
| 17 | 2.0 | 2.0 | 10 | 0.325 | 8.23 | 8.1499 |
| 18 | 2.5 | 0.0 | 20 | 0.400 | 5.45 | 5.5469 |
| 19 | 2.0 | 2.0 | 0 | 0.400 | 7.05 | 7.0371 |
| 20 | 2.5 | 0.0 | 20 | 0.350 | 6.98 | 6.9985 |

**d).Configuration of Network**

The network configuration is defined in terms of the number, size, nodal properties etc., of the input/output vectors and the number of hidden-layers. There is no direct method to select the number of nodes in the hidden-layers.

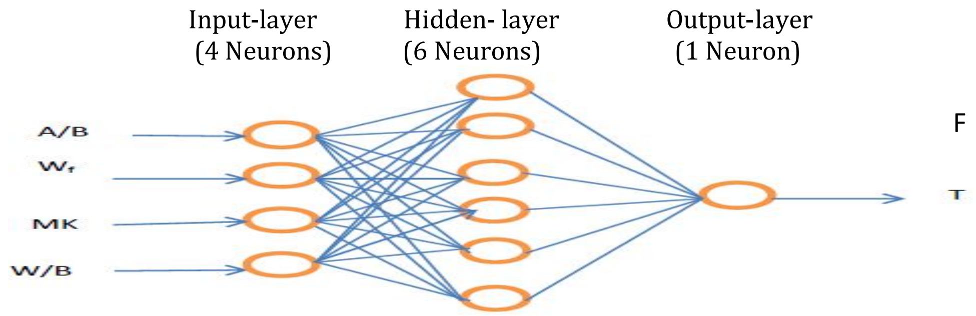


Fig. 1 Configuration of BPN model

Generally, a trial and error method has to be adopted. Hence, several trials are made to find the number of hidden-layers and the number of neurons in each hidden-layer. Initially trial is made with a single hidden-layer consisting of 4 neurons and in the subsequent trails the number of hidden-neurons is increased from 4 to 6. It is found that the network with one hidden-layer training has become successful. Hence, 4-6-1 network configuration is selected for the BPN model, whose architecture is depicted in Fig. 1.

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**e).Training of BPN model**

Training of the network is carried out to map the desired relationship between input and the corresponding output. Initially, the weights and the thresholds matrix are randomly generated using the facility available in the software NNS-BPN. With this weight and threshold matrix, the network is subjected to the traditional back-propagation algorithm. A constant learning rate of 0.6 and a momentum factor of 0.9 are adopted during training. Fig.2 shows the training of BPN model for flexural strength.

The network has been trained for 15000 cycles and the observed progress of training of the network is presented in Table - 3. The root mean square (RMS) error after 15000 training cycles is 0.01015. Consequently, the performance of the network is acknowledged. At this phase the training of the network is ceased to avoid any over training that may shackle the generalization capabilities of the network. The percentage error observed in the training of BPN is 1.653

**Table – 3 Training progress of BPN model**

| S.No. | No. of training epochs | R.M.S error |
|---|---|---|
| 1 | 1000 | 0.08526 |
| 2 | 2000 | 0.04738 |
| 3 | 5000 | 0.02653 |
| 4 | 7500 | 0.01754 |
| 5 | 10000 | 0.01621 |
| 6 | 12500 | 0.01429 |
| 7 | 15000 | 0.01015 |

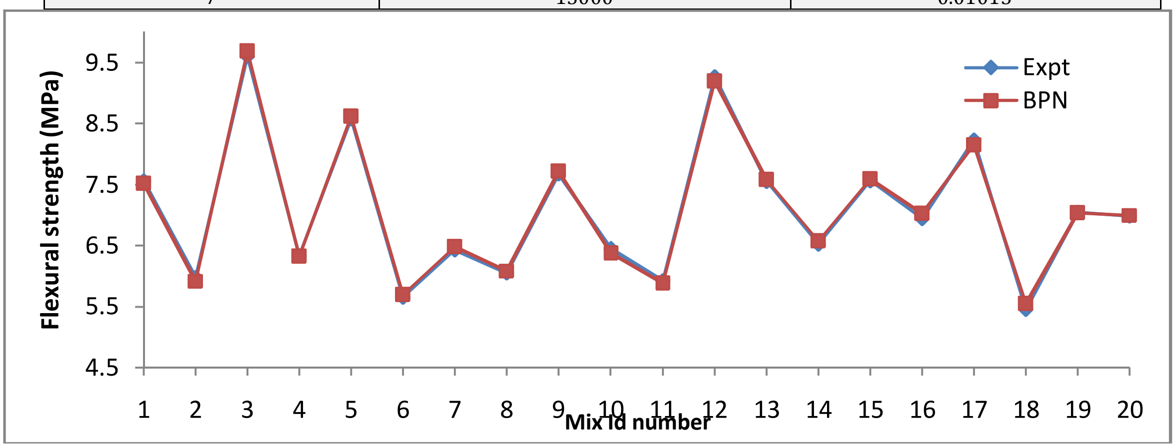


Fig. 2 Training of BPN model for Flexural strength

**f).Validation of network**

Although, the network model has derived successfully the complex relationship between the input parameters and the overall performance for the MK-PFRHPC to evaluate its performance and to generalize the relationship, is tested for unseen problems, i.e. for aggregate-binder ratios, percentage weight of PP fibers, percentage weight of metakaolin and water-binder ratios, outside the training set for its practical use as a macro-mechanical model. The validation of the network model is shown in Fig. 3 and Table – 4

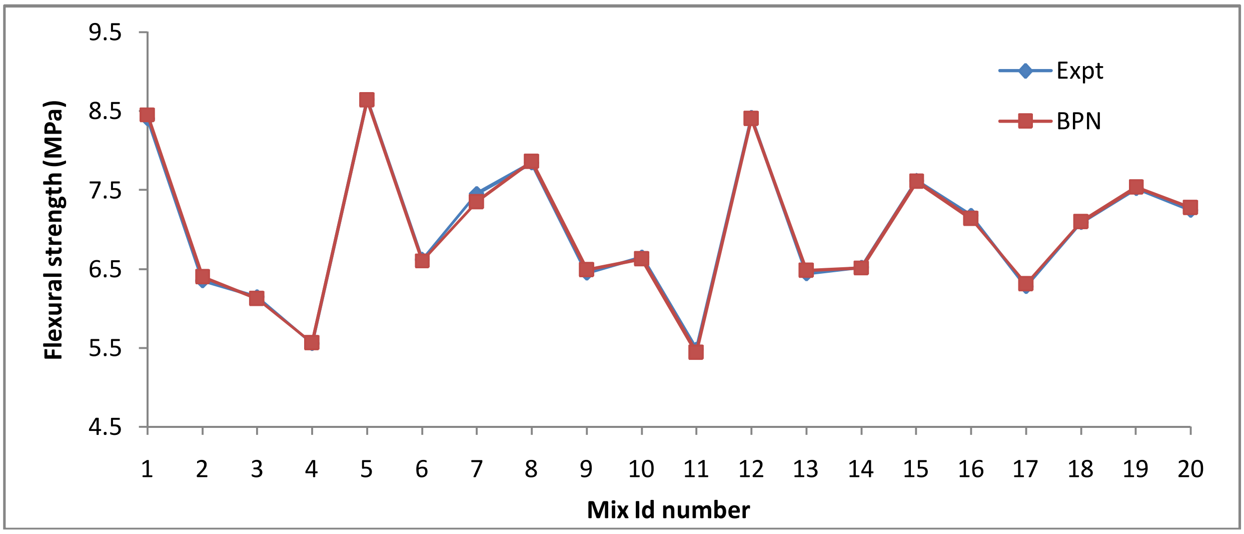


Fig. 3 Validation of BPN model for Flexural strength

i.e. comparison between the experimental and predicted values of flexural strengths by BPN model. The maximum error observed in the validation of BPN model is 1.462 percent.

**Table - 4 Validation of BPN network model**

| Mix Id No. | A/B | $W_f$ | MK | W/B | F | |
|---|---|---|---|---|---|---|
| | | | | | Expt | BPN |
| 1 | 2.0 | 0.0 | 0 | 0.325 | 8.41 | 8.4596 |
| 2 | 2.5 | 2.0 | 0 | 0.350 | 6.35 | 6.3996 |
| 3 | 2.0 | 1.0 | 20 | 0.325 | 6.15 | 6.1279 |
| 4 | 2.5 | 0.5 | 0 | 0.400 | 5.56 | 5.5614 |
| 5 | 2.0 | 0.0 | 10 | 0.325 | 8.65 | 8.6402 |
| 6 | 2.5 | 2.0 | 0 | 0.375 | 6.62 | 6.6085 |
| 7 | 2.0 | 0.0 | 20 | 0.350 | 7.46 | 7.3532 |
| 8 | 2.5 | 0.5 | 30 | 0.375 | 7.85 | 7.8611 |
| 9 | 2.0 | 1.5 | 0 | 0.375 | 6.45 | 6.4883 |
| 10 | 2.5 | 0.0 | 10 | 0.400 | 6.65 | 6.6314 |
| 11 | 2.0 | 0.0 | 30 | 0.350 | 5.48 | 5.4405 |
| 12 | 2.5 | 1.0 | 20 | 0.325 | 8.42 | 8.4085 |
| 13 | 2.0 | 1.5 | 10 | 0.400 | 6.44 | 6.4817 |
| 14 | 2.5 | 0.5 | 0 | 0.375 | 6.52 | 6.5191 |
| 15 | 2.0 | 0.5 | 10 | 0.375 | 7.62 | 7.6103 |
| 16 | 2.5 | 2.0 | 20 | 0.325 | 7.18 | 7.1412 |
| 17 | 2.0 | 2.0 | 10 | 0.325 | 6.28 | 6.3097 |
| 18 | 2.5 | 0.0 | 20 | 0.400 | 7.09 | 7.1025 |
| 19 | 2.0 | 2.0 | 0 | 0.400 | 7.52 | 7.5367 |
| 20 | 2.5 | 0.0 | 20 | 0.350 | 7.25 | 7.2791 |

## CONCLUSIONS

- The relationship between micro-structural parameters, viz. water-binder ratio, and percentage weight of metakaolin, percentage weight of polypropylene fibers and aggregate-binder ratio and macroscopic behavior of MK-PFRHPC is highly complex and non-linear.

- The hidden-layers in the network are selected by observing the learning performance of the one and the two layer networks.
- The training of networks has been continued till the error is reduced to the tolerable limits or until the network stops learning further.
- The performance of network is evaluated for unseen number of examples, which ensured that the network learnt the desired relationship between input and output parameters successfully.
- The neural network approach to the selection of good economical model does not involve any pre-assumptions about the performance of the fiber-reinforced high-performance concrete mix and does not necessitate any pre-assumptions about the material performance, the degree of non-linearity and complexity involved in the problem.
- Once the BPN model captures the relationship between the input and output parameters during training it can predict correctly the performance of any new MK- PFRHPC mixes.
- The percentage error observed in the training of BPN is 1.653 and that in validation of BPN model is 1.462

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