# Prediction of the Behaviours by the Prismatic Beams with Polypropylene Fibers under High Temperature Effects through Artificial Neural Networks

Fatih Altun and Tamer Dirikgil
*Department of Civil Engineering, Erciyes University, Kayseri, Turkey*

Keywords: Polypropylene Fiber, Concrete, High Temperature, Flexure Strength, Multilayer Perceptron, Radial Basis Function Neural Network.

Abstract: In order to improve the mechanical qualities of a concrete, various kinds of fibers are added to the concrete. In the studies, polypropylene (PP) fibers are employed as a fiber type. It has a significant place in the researches that PP fibers not only improve the mechanical qualities of the concrete under normal temperatures, but also prevents the bursting of the concrete with the internal vapour compression under high temperatures. The distributions and locations of the fibers in the concrete and the variables employed for experimental proceedings affect the mechanical results. This makes it difficult to link the obtained results to each other. In order to establish a complicated link, it is inevitable to create a learning mechanism. In this study, multilayered perceptrons (MLP) and radial basis function artificial neural network (RBFNN) models were used and their flexure strengths were sought to be predicted. Both of the neural network models put in a successful performance and enabled the prediction of the experimental results with a satisfying approximation.

## 1 INTRODUCTION

It is practically not possible to empirically state the effects of locations of the fibers, homogeneity of the fibers and the different temperatures on the mechanical qualities of a concrete. Therefore, it is complicated to predict the behaviours of the concrete with similar qualities by the data in hand. To model and anticipate the complicated systems depending on the input-output data and/or unknown behaviours, methods to develop mathematical models in various fields of civil engineering have been employed (Astrom and Eykhoff, 1971).

In this study, bending tensile strengths of the concrete with PP fiber addition are predicted using the multilayered perceptron neural network and radial basis function artificial neural network models. For both of the models, the same input, validation, and testing data were used. Addition of split tensile strength obtained through experimental studies to the variables on which experimental proceedings were applied in the entry parameters made it more difficult to link between the input-output data. Ultimately, the performance of the two different artificial neural network models was found to be satisfying.

## 2 EXPERIMENTAL PROCEDURE

The samples produced during the experimental study comprised of members with 40 MPa characteristic compressive strength and in the C35/45 concrete class (TS EN 206/1, 2002). Samples were cured in periods of 7,28 and 90 days and made ready. In addition to the room temperature (24.5 ºC), five more temperature effects of 100 ºC, 200 ºC, 400 ºC, 600 ºC and 800 ºC were employed. The samples under the room temperature were assessed as the reference samples for the other temperature effects.
Following the heating period, the temperature in the oven was left to cool by itself with its lid closed until it decreased to room temperature in order to keep the experimental samples from exposing to the effects of abrupt temperature changes. Table 1 and Table 2 shows the 216 cylinder and prismatic samples according to each fiber type, volumetric fiber ratio, and cure period and temperature value.

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Table 1: Cyclindrical Samples.

| Cyclindrical Samples (150x300mm) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Day | Temp. (°C) | Polypropylene Fiber Ratio (% Volumetrical) FP ; MFP | | | | | |
| | | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
| 7, 28, 90 | 24.5 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 100 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 200 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 400 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 600 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 800 | 1 | 1 | 1 | 1 | 1 | 1 |
| Total | 2x6x3x6=216 | | | | | | |

Table 2: Prismatic Samples.

| Prismatic Samples (150x150x750mm) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Day | Temp. (°C) | Polypropylene Fiber Ratio (% Volumetrical) FP ; MFP | | | | | |
| | | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
| 7, 28, 90 | 24.5 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 100 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 200 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 400 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 600 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 800 | 1 | 1 | 1 | 1 | 1 | 1 |
| Total | 2x6x3x6=216 | | | | | | |

## 3 EXPERIMENTAL RESULTS

Addition of polypropylene fibers improved the bending strength of the sample until 200ºC, but in the samples that had been exposed to higher temperatures, the change in the fiber ratio had no contribution. With the increase in the cure period of the sample, bending strength of the samples increased. In the Figures 1-3 the bending strengths of the prismatic samples for 7, 28 and 90 days are given respectively.

Under high temperature values, bending strength decreased also together with the increase in the fiber ratio. Therefore, it can be stated that the local caverns created by the melting PP fibers in the sample adversely affect the behaviour of a member when bending. The Multifilament Polypropylene (MFP) fibers did not contribute to the bending strengths of the samples under the room temperature and 100 ºC as much as the Flament (FP) fibers did. As the MFB fiber ratio increased, the bending strength was observed to decrease. However, the bending strength of the samples with MFP above 200ºC temperature values was measured to be higher than those with FP fibers.

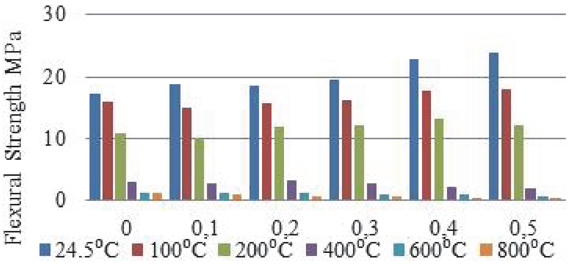


Figure 1: Flexural Strength of Prismatic Samples-7 Days.

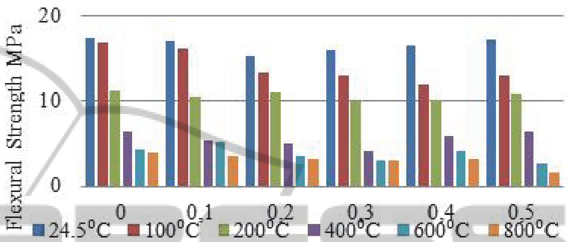


Figure 2: Flexural Strength of Prismatic Samples-28 Days.



## 4 ARTIFICIAL NEURAL NETWORK MODELS

For the prediction of the experimental data obtained from the study, MLP artificial neural network model and RBF neural network models were used. Considering the error values and determination coefficients between the observed and predicted data, the performance of the models were evaluated together.

In the first place, the experimental parameters to be used in the models were identified and then the training, validation and testing data were classified. A total of 512 samples with different fiber types, fiber ratios, and cure periods and which were exposed to different temperature effects were evaluated. Of the 512 samples, 216 were cylinder samples with a size of 150x150x300 each and the other 216 were prismatic samples with a size of 150x150x300mm each produced with the same concrete mixture. Therefore, in the applications, evaluations were made for the compression strengths of 216 cylinder samples and the bending tensile strength of the prismatic samples with the same materialistic qualities.

In each model, considering the same input parameters, 5 input parameters were used. Under the light of these data, the prediction for 1 output parameter was made and its error ratio and correlations were evaluated. The input parameters were set as the fiber type used to prepare the sample

Table 5: Error values for MLP performance.

| Hidden Layer | Number of first layer neuron | Transfer Function | $R^2$ | MSE | RMSE | MAE | MARE |
|---|---|---|---|---|---|---|---|
| 3 | 6 | tansig-logsig-logsig-tansig | 0.9734 | 0.6990 | 0.8361 | 0.5594 | 14.7446 |
| **2** | 5 | logsig-logsig-tansig | 0.9804 | 0.5099 | 0.7140 | 0.5063 | 14.6786 |
| 1 | 6 | tansig- logsig | 0.9826 | 0.4614 | 0.6793 | 0.5095 | 18.4026 |

mixtures (Ft), the split tensile strength of the cylinder samples (sfc), volumetric fiber ratio in the mixture (FR), temperature (T), and cure period (Cp).

The output parameter is the bending strength of the prismatic samples (Md). The 216 data used in themodel were classified with random selection 60% reserved for training, 20% for validation and 20% for testing phases. In order to make the models learn the same data and predict the same test data, the same training, validation and testing data were used in both models.

The data used in the artificial Neural networks were normalized first and then scaled.

## 4.1 Multilayer Perceptron (MLP)

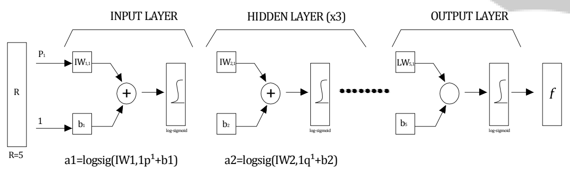


Figure 3: Example architecture for one of the MLP models.

For the design of MLP model, the number of neurons in the hidden layer, activation (transfer) function and the learning algorithm are of importance. In the study, the MLP neural network model was created in three forms using 3,2 and 1 hidden layers (Figure 4). The table 5 shows the transfer function between the input layer and first two hidden layers and the transfer functions whereby the best prediction results were obtained between the input layer and hidden layers. The transfer function for the output layer is called "purelin". As for the learning function, it is the "trainlm" function which updates its tendency values and weights according to Levenberg-Marquart optimization. "Trainlm" is a very quick learning function but needs a great deal of memory for analysis (Matlab Software, R2009b).

The Figures 4, 5, and 6 show the performance of the model depending on the values predicted during the training, verifying and testing phases and the correlation between the targeted values

The Figure 7 presents the fluctuation graph between the values obtained during the testing phase and the targeted values.

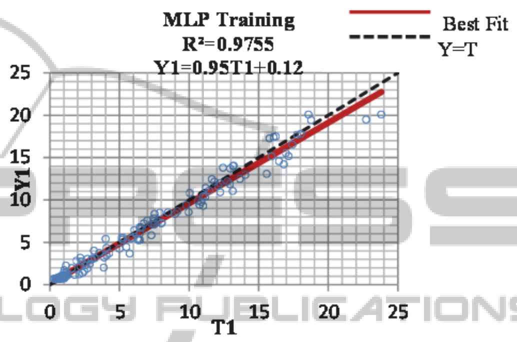


Figure 4: MLP correlation of training.

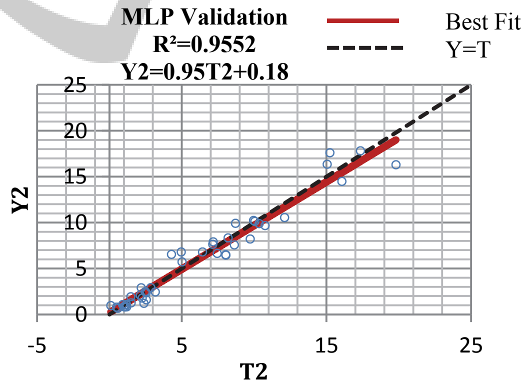


Figure 5: MLP correlation of validation.

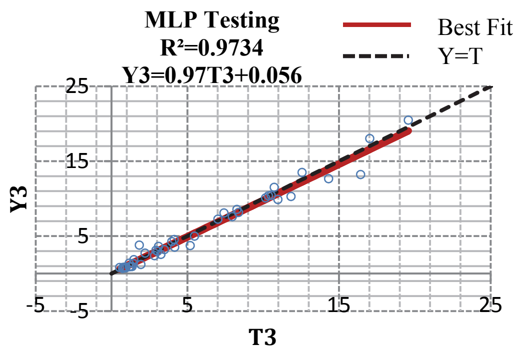


Figure 6: MLP correlation of testing.

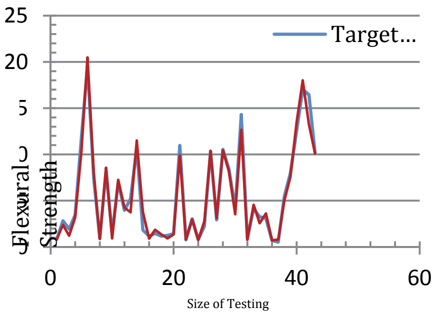


Figure 7: Coherence between target and predicted values for MLP.

## 4.2 Radial Basis Function ANN (RBFNN)

30 neurons have been used in this model.

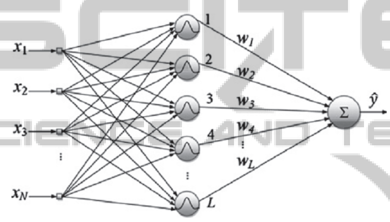


Figure 8: Typical Radial Basis Function ANN (Alexandridis et al., 2012).

Table 6 shows the error values obtained from the radial basis neural networks

Figures 9, 10 and 11 present the performance depending on the correlation between the values predicted during the training, verifying and testing phases and targeted values.

Table 7 states the obtained results from the models and experimental data. Moreover, Table 8 states the mean absolute errors between the real and predicted values for each data.

Table 6: Error values for RBFNN performance.

| RBFNN | $R^2$ | MSE | RMSE | MAE | MARE |
|---|---|---|---|---|---|
| Testing | 0.9581 | 0.6456 | 0.8035 | 0.5572 | 14.5678 |

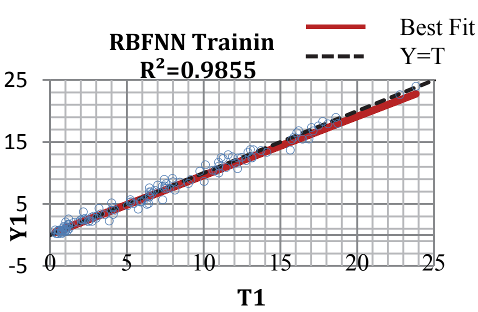


Figure 9: RBFNN correlation of training.

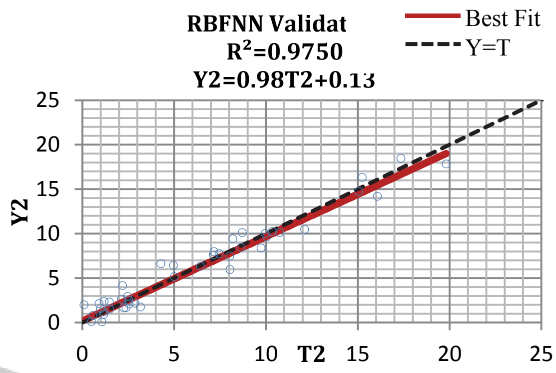


Figure 10: RBFNN correlation of validation

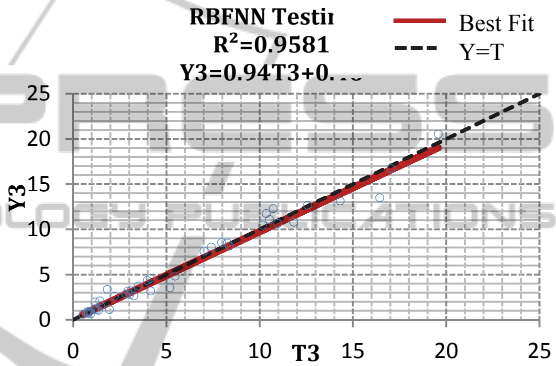


Figure 11: RBFNN correlation of testing.

Table 7: Obtained results from the models and experimental data.

| Model | $R^2$ | MSE | RMSE | MAE | MARE |
|---|---|---|---|---|---|
| MLP Testing | 0.9734 | 0.5099 | 0.7140 | 0.5063 | 14.6786 |
| RBFNN Testing | 0.9581 | 0.6456 | 0.8035 | 0.5572 | 14.5678 |

# 5 CONCLUSIONS

This study followed the transformations in the mechanical qualities of the concrete with polypropylene fiber addition when exposed to temperature and evaluated this transformation via artificial neural networks. The link between the transformation in the split tensile strength, cure period, fiber type and temperature parameters and bending strength has been provided.

Both of the models performed well in predicting the experimental data of the bending strength. The single hidden layer used in the multi layered model created a fairly good correlation between the data. However, as the error margin for predicting the small values within the target values was wide, mean absolute relative error was found to be relatively higher. When two hidden layers were used, smaller MARE and MAE values were obtained. Three hidden layers led to a decrease in the correlation and to an additional increase in the errors. However, error values were smaller than those in the single hidden layered model. As the number of the hidden layers increased, it caused the predictions to diverge from the target as it increased the amount of weight coefficients.

The mean absolute relative error values obtained from the radial basis function neural network model were lower. As such, it can be said that the model is more successful in predicting the small target values with less errors. However, the higher numbers of mean absolute and square errors implicates that the performance of the model was a little bit worse. As the data to be predicted by the models were randomly arrayed, there occurred an abrupt increase or decrease between the previous values and the following values. These changes led to a decrease in the prediction performance and an increase in the model errors. The error ratios of the radial basis network resulting from these abrupt data changes were lower than the multilayered network.

Both of the neural network models used in this study performed successfully and enabled the prediction of experimental values with satisfying approximation.

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