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# Modelling of Multi Layer Feed forward Neural Networks to Determine the Compressive Strength of Marmara Region Aggregate's Concrete

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**Abstract** We aim to estimate concrete compressive strength by using the physical properties of the aggregates that are the main components of concrete. For this aim, concrete samples were prepared with aggregates having different origins and characteristics obtained from different 10 locations of the Marmara region. The compressive strength's results obtained by changing the aggregates were compared by ensuring the other components forming the concrete remained constant. 330 separate experiments were conducted to determine the physical characteristics of the aggregates, and these characteristics were used as input data in a multi layer Feed Forward Network model. The compressive strength of 7 and 28 days of the concrete obtained from the experiments were used as output in to a Multi-layer Feed Forward model. The training and test results from the models coincided closely with experimental results; also, the results were compared to the estimations made with a linear regression method.

**Keywords** Aggregate, Multi Layer Feed Forward Neural Network, Compressive Strength

## 1. Introduction

The reason that the values of concrete's compressive strength are based building designs is that compressive loads are very important. It is only possible to determine the effect of the physical and mechanical characteristics of aggregate to the concrete's compressive strength with experiments. Such studies take a long time and are not economical. Therefore, the different estimation methods are formed using past empirical studies in order to determine the concrete compressive strength.

Artificial neural networks (ANN) are frequently used to determine concrete's physical and mechanical characteristics. Lai and Serra (1997) estimated the compressive strength over 28 days of different mixtures of concrete with an ANN model. In the study, they obtained values of the compressive strength in varied learning rates, in various network neurons and they determined that the results were very close to each other [1]. Mukherjee and Biswas (1997) developed an ANN model that is five neurons in each layer, with two hidden layers by using the perception network and back propagation algorithms in order to estimate the mechanical behaviour of the concrete at high temperature [2]. They estimated the stretching transformation relationship of the material at high temperature and obtained the results that were similar to experimental results. Yeh (1998) used the values of day, fine aggregate, course aggregate, super plasticizer, water, fly ash, and cement as data in an adaptive ANN model in order to estimate the compressive strength of concrete [3]. Hong-Guang and Ji-Zong (2000) estimated the compressive strength by using a multi layer perceptron ANN; they used quantity of the chemical additive, slump, aggregate/cement, sand/aggregate, fineness module, the greatest dimension of aggregate, cement, water, water, cement and type of cement as input data into the model [4].

Dias and Pooliyadda (2001) formed an ANN and multi regression model in order to estimate the compressive strength and slump rate of concrete and compared the results to $r^2$ (coefficient of multiple correlation) statistical values. They determined in their study that $r^2$ values in the ANN models were better than $r^2$ values found with the multi regression models [5]. Akkurt et al. (2003) developed a model to estimate the compressive strength of cement mortar with ANN and showed that it would be able estimate the compressive strength of the cement mortars and the very small rates of error with ANN model [6]. Lee (2003) formed models by using multi neural networks and single neural networks in order to estimate the compressive strength in the different hours and days by using ANN; they determined that the experimental results and their results obtained from the models were compatible [7]. Baykasoglu et al.(2004) estimated the compressive strength of cement mortar of 28 days by using genetic programming techniques and regression analysis methods and observed that the best result was from values obtained from an ANN model in

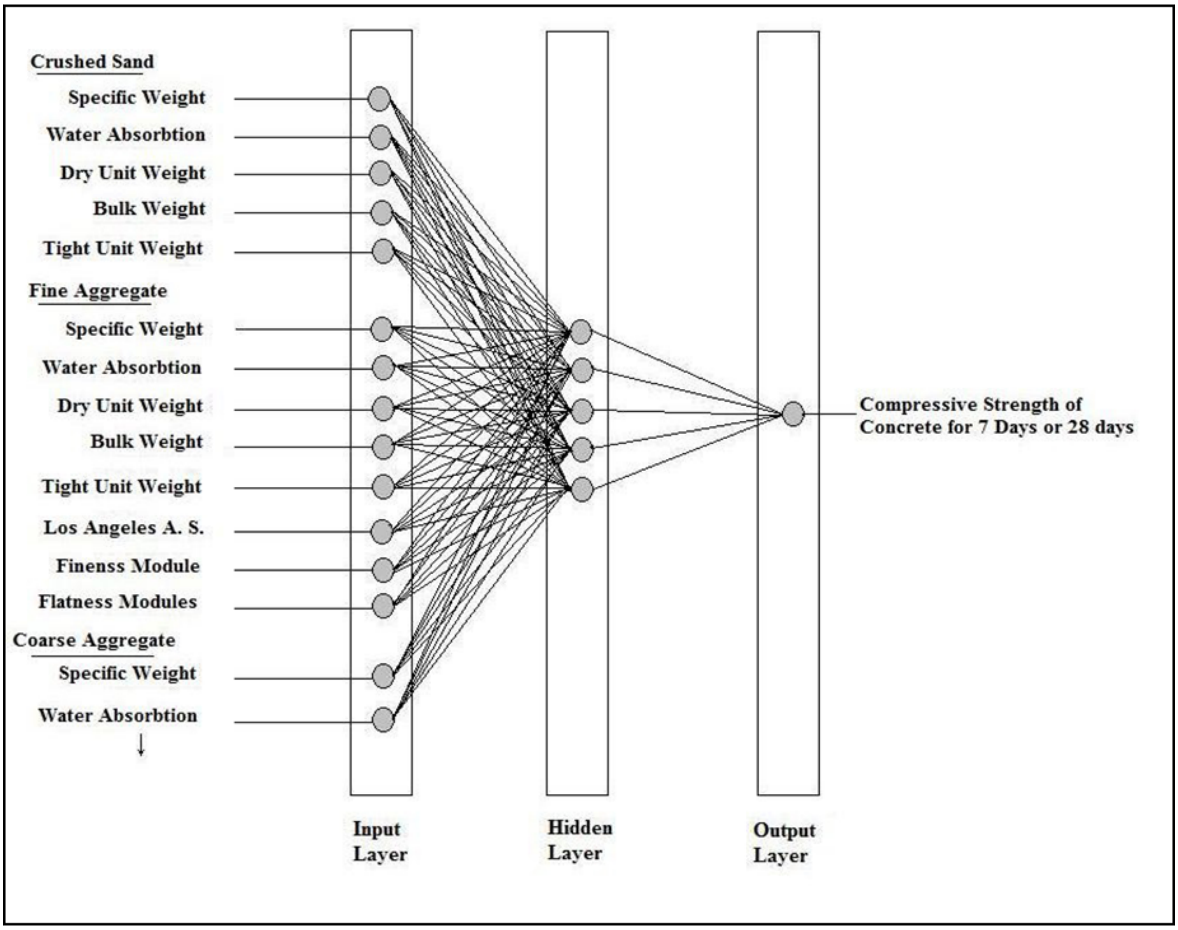


**Figure 2**. Multi layer feed forward network structure for predicting the compressive strength [17].

# 3. Experimental Studies and Data Preparation

The aggregates used in the production of concrete were basically assured from 10 different aggregate pits. Their physical characteristics were separately based in modelling by separating each sample of aggregates into three classes of dimensions in conformity with the concrete's production standard.

The physical and mechanical characteristics of the aggregate forming the concrete were represented with 20 different parameters (Table 1.).

These parameters determining the aggregate's characteristics were used as the entry parameters in the artificial neural network. Consequently, both network input layers determining the concrete resistances of 7 days and 28 days consist of 20 neurons (Table 2.).

The data obtained from the results of 330 compressive strength experiments were used in the model. In experiments, the amounts of cement, water, ash, crushed sand, plasticizer, fine aggregate, and course aggregate remained constant in weight (Table 3.). 250 pieces of 330 data in total, obtained experimentally, were separated for training; the remaining 80 data were used for testing in order to estimate the compressive strength with the network [17].

As there is only the concrete strength as the output parameter in the exit of network, in both Multi layer feed forward network models there is only one neuron in the exit layer. It was observed that the hidden layered network model with five neurons showed the best performance after the number of neurons in the hidden layer and the number of the hidden layer's neurons in different numbers were tried experimentally as there was not any absolute analytic rule in order to determine the number of neurons in the hidden layer; consequently, the number of neurons of the hidden layer were also determined as 5 for both models.

Its performance decreased significantly when it was operated with the test data, while the performance of model was high in the training stage; also, the performance of the network was high in the training stage when the number of neurons of the hidden layer was selected greater than 5. The network's total square error did not decrease under a specific value when the number of neurons of the hidden layer was selected to be less than 5. Consequently, the network's learning capacity was not enough to learn the relationship between the output parameters and the input parameters used in the problem when the network's hidden layer was designed with less than 5 neurons.

**Table 1.** Multi layer feed forward Network model architecture

| Data set | 330 Aggregate samples for Compressive Strength Test obtained from 10 different location | | | | |
|---|---|---|---|---|---|
| Input Parameters | Crushed sand (KK-1) | Specific weight, Water absorption, Dry unit weight, Bulk weight, Tight unit weight | | Output Parameters | Compressive strength |
| | Fine aggregate (K-1) | Specific weight, Water absorption, Dry unit weight, Bulk weight, Tight unit weight, Fineness module, Flatness module | | | |
| | Coarse aggregate (K-2) | Specific weight, Water absorption, Dry unit weight, Bulk weight, Tight unit weight, Los Angeles A.S., Fineness module, Flatness module | | | |
| | | | | | |
| Activation Function | Sigmoid Function | | Number of input layer neurons | | 20 |
| Performance function | MAPE | | Number of hidden layer and neurons | | 1 and 5 |
| Number Of layer | 3 | | Number of output layer and neuron | | 1 and 1 |

**Table 2.** A part of imput data set from aggregate properties

| Parameters | Agg. Kodes | Loc. 1 | Loc. 2 | Loc. 3 | Loc. 4 | Loc. 5 | Loc. 6 | Loc. 7 | Loc. 8 | Loc. 9 | Loc. 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Specific weight(gr/cm3) | KK-1 | 2.70 | 2.74 | 2.68 | 2.75 | 2.64 | 2.71 | 2.77 | 2.69 | 2.66 | 2.61 |
| | K-1 | 2.71 | 2.72 | 2.73 | 2.73 | 2.67 | 2.73 | 2.71 | 2.68 | 2.68 | 2.71 |
| | K-2 | 2.71 | 2.75 | 2.72 | 2.71 | 2.68 | 2.71 | 2.71 | 2.70 | 2.74 | 2.67 |
| Water absorption (%) | KK-1 | 1.30 | 1.68 | 1.24 | 0.95 | 2.15 | 1.09 | 1.65 | 1.32 | 0.92 | 1.62 |
| | K-1 | 0.70 | 0.41 | 0.78 | 0.48 | 0.92 | 0.32 | 0.82 | 0.53 | 0.88 | 0.52 |
| | K-2 | 0.40 | 0.28 | 0.42 | 0.36 | 1.56 | 0.19 | 0.25 | 0.26 | 0.37 | 0.27 |
| Dry unit weight (gr/cm3) | KK-1 | 2.68 | 2.67 | 2.65 | 2.68 | 2.61 | 2.69 | 2.68 | 2.65 | 2.66 | 2.63 |
| | K-1 | 2.70 | 2.68 | 2.71 | 2.69 | 2.78 | 2.73 | 2.69 | 2.68 | 2.72 | 2.75 |
| | K-2 | 2.71 | 2.74 | 2.70 | 2.74 | 2.75 | 2.69 | 2.75 | 2.72 | 2.70 | 2.73 |
| Bulk weight (gr/cm3) | KK-1 | 1.59 | 1.47 | 1.28 | 1.47 | 1.75 | 1.69 | 1.32 | 1.57 | 1.63 | 1.64 |
| | K-1 | 1.45 | 1.36 | 1.29 | 1.47 | 1.48 | 1.39 | 1.36 | 1.41 | 1.49 | 1.47 |
| | K-2 | 1.44 | 1.34 | 1.41 | 1.45 | 1.43 | 1.46 | 1.51 | 1.36 | 1.39 | 1.36 |
| Tight unit weight (gr/cm3) | KK-1 | 1.67 | 1.63 | 1.49 | 1.62 | 1.83 | 1.79 | 1.52 | 1.72 | 1.75 | 1.76 |
| | K-1 | 1.71 | 1.67 | 1.53 | 1.74 | 1.75 | 1.71 | 1.61 | 1.63 | 1.76 | 1.81 |
| | K-2 | 1.83 | 1.64 | 1.77 | 1.82 | 1.81 | 1.77 | 1.81 | 1.69 | 1.71 | 1.88 |
| Los Angeles A.S | K-2 | 21.70 | 21.70 | 19.70 | 18.20 | 26.30 | 15.60 | 18.30 | 24.50 | 22.30 | 22.50 |
| Fineness module (%) | K-1 | 5.55 | 4.75 | 5.68 | 5.57 | 5.75 | 5.48 | 6.15 | 5.60 | 4.95 | 5.64 |
| | K-2 | 6.82 | 6.79 | 6.59 | 6.81 | 6.20 | 6.72 | 6.79 | 7.08 | 6.28 | 6.42 |
| Flatness module (%) | K-1 | 14.00 | 11.00 | 12.00 | 16.00 | 15.00 | 13.00 | 15.00 | 14.00 | 15.00 | 13.00 |
| | K-2 | 12.00 | 10.00 | 9.00 | 14.00 | 11.00 | 13.00 | 16.00 | 14.00 | 12.00 | 9.00 |

**Table 3**. Weighted Distribution of Concrete Construction Materials [16]

| Material | Quantity($kg/m^3$) |
|---|---|
| Cement | 260-275 kg |
| Water | 185-195 Kg |
| Ash | 67-72 Kg |
| River Sand | 565-573 Kg |
| Crushed Sand | 200-210 Kg |
| I No fine Agregate | 550-565 Kg |
| II. No coarse Agregate | 485-490 Kg |
| Additive (Plasticizer) | 2,7 Kg |

# 4. Results and Evaluations

The results obtained from the network model and linear regression and experimental studies are given in Table 4. The correlation coefficient between the results of the network and experimental studies for 7 days is 0,717; for 28 days, the correlation coefficient is 0,926. This shows that the results of multi layer Feed Forward Network (MLFFN) are close to the result of the experimental studies.

The correlation coefficient and mean absolute percent error are used to control the performance of the neural network approach in predicting the compressive strength.The results of the compressive strengths for 7 days, which were obtained from the multi layer Feed Forward Network model, represent the actual values with an average of 96,2 %. The values of the compressive strengths for 28 days had been forecasted with 2,8 % error value in the multi layer Feed Forward Network model, which means that the results had been forecasted with a 97,2 % value of truth. But, the Mape values in the linear regression is more than 9 % for the values of 28 days and 11,6 % for the values of 7 days, as shown in Figure 3.

The multi layer Feed Forward Network results are compared with the results of experimental values; they show that multi layer Feed Forward Network results complied with experimental results with a small ratio of 2,8 % mean absolute percent error. Error analysis is based on mean absolute percent error.

In the same manner, the average MAPE of the linear regression results to the results of experimental studies is 11.62%.

We compared the $r^2$ value between the linear regression technique and results of experimental studies. This shows that for linear regression had been forecasted values of 0,479 – 0,551 ratios but it had been seen successfully forecasted with approximately $R^2$ values of 0,733 for 7 days and 0,740 for 28 days with the MLFFN. Comparison of experimental studies with MLFFN and LR results are given in Figure 4, 5, 6 and 7 for two different locations.

## 5. Conclusions

In this study, the estimation models were developed with the artificial neural networks as alternative approaches for determining the compressive strength of concrete produced from ten different aggregates taken from ten different regions in laboratory experiments, and the results were compared to the linear regression results.

Results obtained from experimental studies and MLFFN results were very close to each other; also, linear regression results gave worse performance.

In order to obtain better results for the learning and estimation stages of the model, it is important to include more data in the model.

As a result, experimental studies are the works, which are realized in long periods, but they are expensive, since they require more expenses and materials to be spent and more technical personnel to be employed. Thus, these losses and requirements of the experimental studies can be minimized by using of artificial neural networks models.

Artificial neural networks are inspired by biological central nervous systems of brain and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. ANN has the ability to implicitly detect complex nonlinear relationships between dependent and independent variables, with learning algorithm is widely used in solving various classifications and forecasting problems.

**Figure 3.** Mean Absolute Percent Error of ANN and LR.

**Table 4.** Experimental results and output data of MLFFN and LR.

| Exper. Results Mpa | | MLFFN Reults Mpa | | Linear Reg. Results Mpa | |
|---|---|---|---|---|---|
| 7 days | 28 days | 7 days | 28 days | 7 days | 28 days |
| 30.16 | 38.54 | 30.10 | 39.05 | 33.44 | 35.07 |
| 28.48 | 38.86 | 28.71 | 40.53 | 26.76 | 41.39 |
| 29.26 | 35.77 | 28.41 | 36.90 | 31.54 | 34.30 |
| 29.32 | 38.52 | 28.70 | 37.20 | 29.60 | 34.05 |
| 29.26 | 38.72 | 29.43 | 38.74 | 31.54 | 36.25 |
| 29.36 | 38.94 | 29.21 | 38.99 | 30.64 | 39.47 |
| 29.62 | 43.75 | 28.94 | 42.86 | 29.90 | 47.28 |
| 28.37 | 38.44 | 28.42 | 37.76 | 25.65 | 34.75 |
| 30.99 | 40.04 | 31.36 | 40.37 | 32.27 | 43.57 |
| 27.85 | 35.82 | 28.82 | 37.25 | 26.13 | 39.35 |
| 30.52 | 38.72 | 29.26 | 39.33 | 33.80 | 37.25 |
| 29.20 | 38.56 | 29.96 | 37.65 | 26.48 | 35.09 |
| 26.39 | 43.40 | 25.93 | 44.20 | 28.67 | 46.93 |
| 28.86 | 38.52 | 28.57 | 38.08 | 29.14 | 37.05 |
| 29.16 | 38.22 | 30.08 | 40.03 | 26.44 | 37.75 |
| 27.24 | 42.35 | 25.46 | 41.14 | 29.52 | 42.88 |
| 25.14 | 38.29 | 25.33 | 41.41 | 25.42 | 38.82 |
| 28.76 | 39.83 | 28.72 | 38.63 | 29.04 | 42.36 |
| 29.82 | 43.75 | 30.56 | 42.46 | 30.10 | 44.28 |
| 30.14 | 43.88 | 30.58 | 42.05 | 35.42 | 49.41 |
| 27.14 | 39.22 | 27.29 | 38.66 | 23.42 | 44.75 |
| 28.94 | 38.66 | 30.18 | 38.69 | 33.22 | 33.19 |
| 31.21 | 39.82 | 31.91 | 40.15 | 34.49 | 35.35 |
| 28.35 | 39.04 | 28.70 | 37.55 | 26.63 | 33.57 |
| 29.68 | 38.88 | 30.84 | 41.66 | 31.96 | 39.41 |
| 28.82 | 42.62 | 28.09 | 44.00 | 28.10 | 46.15 |
| 28.73 | 45.62 | 29.95 | 44.22 | 30.01 | 50.17 |

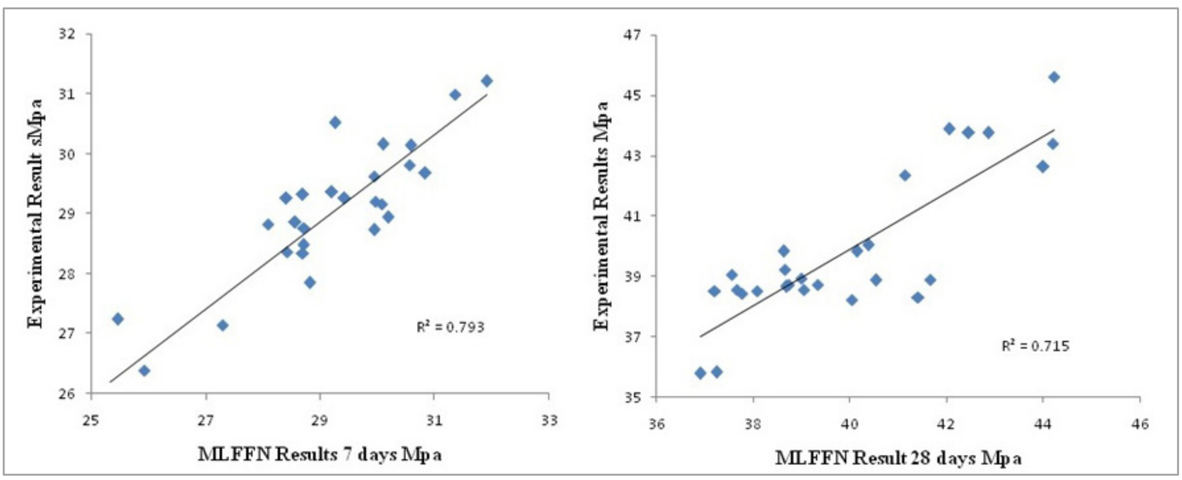


**Figure 4.** Comparison of the Experimental Results and the Results Obtained from MLFFN Model for location 1.

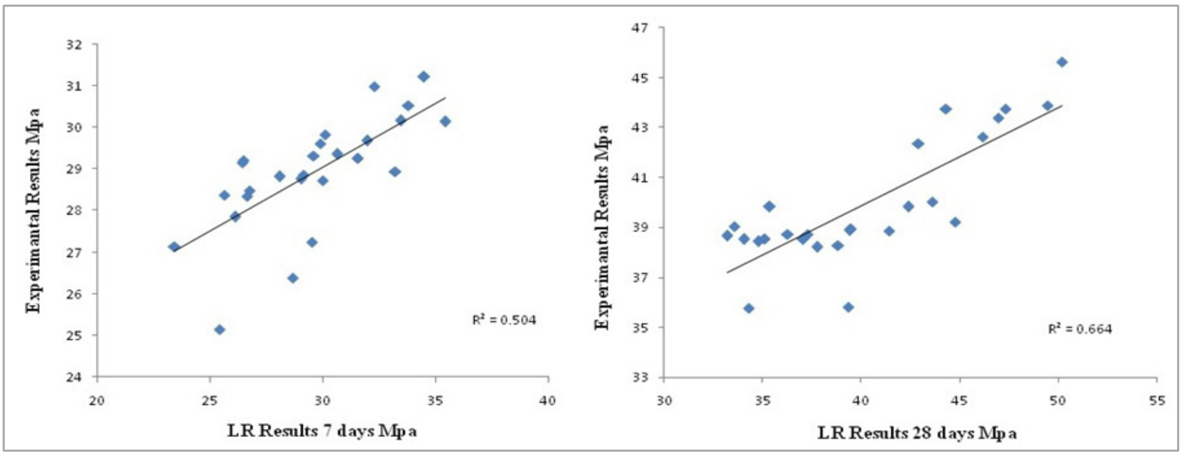


**Figure 5**. Comparison of the Experimental Results and the Results Obtained from LR for location 1.

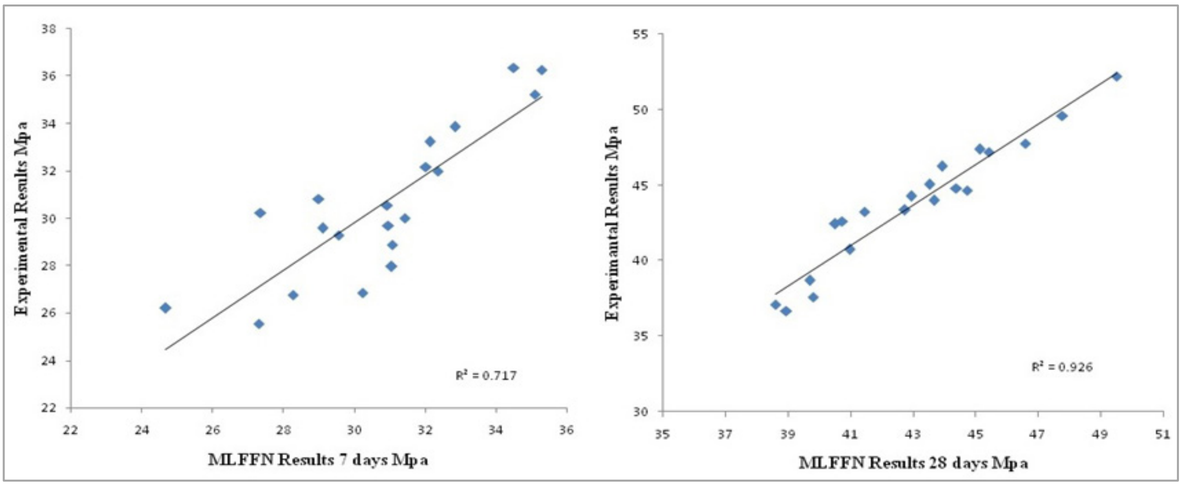


**Figure 6.** Comparison of the Experimental Results and the Results Obtained from MLFFN Model for location 2.

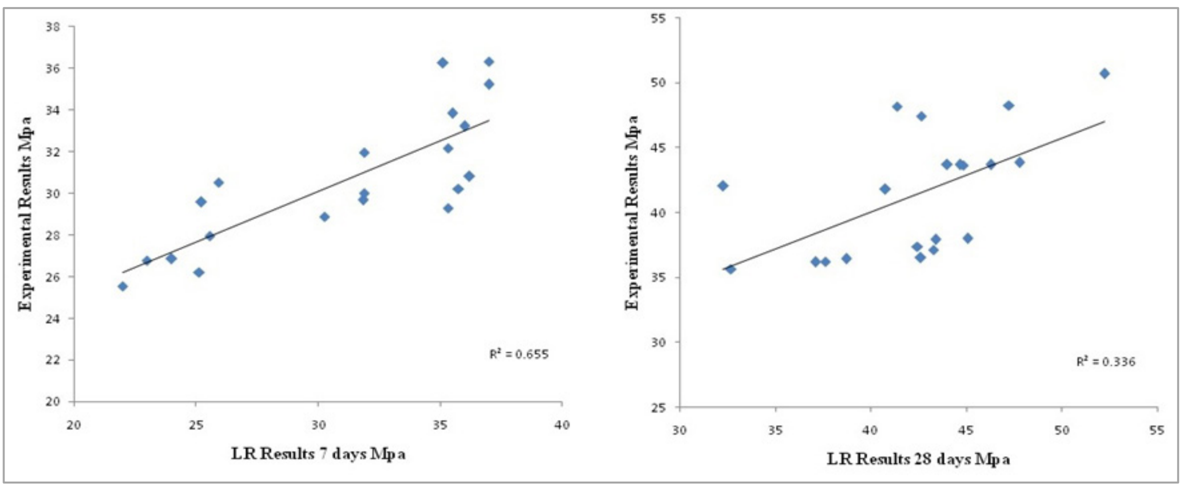


**Figure 7**. Comparison of the Experimental Results and the Results Obtained from LR for location 2.

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