Fuzzy Neural Network Utilization in Prediction of Compressive Strength of Slag-Cement Based Mortars

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Abstract: Compressive strength of mortars is the major property that defines its quality during manufacturing and it is the most common performance measurement used by engineers in designing buildings and other structures. In this study, we used hybrid intelligent system called Neuro-Fuzzy systems that is a combination of Neural Network and Fuzzy Logic to predict the compressive strength of mortars containing GGBFS at 28 days. 52 specimens of high workability and high performance slag-cement based mortars were utilized to train and evaluate this system. The model was constructed and implemented in MATLAB software. Consequently, to verify the usefulness of the model, the predicted outputs from Neuro-Fuzzy model were compared with laboratory results. The results showed that the trained system has strong potential capability to predict compressive strength of mortars containing GGBFS. It shows its potential among other methods used in prediction of Compressive strength of mortars.

Key words: Fuzzy Logic, Neural Network, Neuro-Fuzzy System, Mortars, GGBFS, Compressive Strength

INTRODUCTION

The predictions of the compressive strength or peak stress, $f_{\text{cm}}$, have been a subject of various researches, both analytical and experimental (Francis Oluokun, Manish et al., 2006). The main objective of these simulations is to understand qualitatively the effects of various parameters on the peak stress of Slag-Cement Based Mortars. In laboratory, to obtain the desired mortars strength with suitable workability, there is usually a need to repeat the same process of the testing until the results meet the required specifications. The conventional mathematic modeling process with regression analysis is also not yet available in design codes to accurately predict the compressive strength. Predicting compressive strength by mathematical modeling can be assessed by technique-based on the empirical relationship between a single parameter and compressive strength, but such an assessment would be more accurate and more reliable if it were based on several parameters as pointed out before. Although this has been endeavored but because of the poor accuracy of such assessments (e.g. multiple correlation or graphic techniques), due to the lack of a proper computing tool, the assessment are not yet available in design codes to predict the compressive strength of mortar accurately (Zeli, Ru and Krstulovi, 2004; Kheder et al., Zain and Abd). Therefore, there is a real need to seek for alternatives such as computer-based methods to improve the prediction of compressive strength of mortars.

Artificial Neural Networks (ANNs) are powerful computing tools which were inspired by the neural architecture of the human brain (Warren S. McCulloch and Walter Pitts) can be used for this prediction. The human brain consists of densely interconnected set of nerve cells that is processing unit called neurons. ANNs adapt solutions and are capable of learning the interrelationships among multiple variables by simply presenting them with data. In the last decade, ANNs have started to be used in the modeling of various civil engineering systems and their components (Hola and Schabowicz, 2005; Pala et al., 2007; Tsoukalas and Uhrig, 1997; Kartam et al., 1997; Rajasekaran et al., 1996; Amir Ali MoavenShahidi, 2009; Fadare and Ofidhe, 2009; Baan and Jutten, 2000). One advantage of ANN modeling is that there is no need to know a priori the functional relationship among the various variables involved, unlike in regression analysis. The ANNs automatically construct the relationships for a given network architecture as experimental data are processed through a learning algorithm. This type of computing tool can be improved by hybridizing it with other methods.

Fuzzy Logic (FL) is not logic that is fuzzy, but logic that is used to describe fuzziness. FL is the theory of fuzzy sets that calibrate vagueness. The FL concept (also called fuzzy set theory) is based on all things that admit of degrees such as temperature, weather, speed and so on. On the other side the boolean or conventional logic draws line between members and non-member of a class. For instance, we said that the motor is running...
fast and for the membership of the fast set it 80% belongs to the fast set. FL reflects the way of human thinking about words and the sense of that. In this type of logic, it shows the value as a real number between 0 and 1 instead of false or true (0 or 1) values to show the membership value of a set. However, the FL cannot help in such prediction like Compressive Strength of Slag-Cement Based Mortars.

In fact, the hybrid system which is used both ANN and FL can be an accurate system to predict the Compressive Strength of Slag-Cement Based Mortars. The evaluation of this system shows the capability of such system with specified parameters for the prediction based on the proper learning and testing dataset. The remainder of this paper is organized as follows. In the following section, we present two different combined methods. In subsection 2.1 ANN model, in subsection 2.2 FL, and in 2.3 the hybrid methodology Neuro-Fuzzy Logic system have been described.

**Fuzzy Logic and Artificial Neural Network Concepts:**
A close relationship exists between ANN and FL systems since they both work with degrees of imprecision in a space that is not defined by sharp deterministic boundaries. FL and ANN technology can be fused into a unified methodology known as Neuro-Fuzzy system to become more accurate and practical. This kind of systems demonstrate proper power of computationally in different areas (PejmanTahmasebi, 2010; Akbarzadeh et al., 2009; Khosravi and Llobet et. al. 2007; Mora, et al., 2006; Chunju et al 2007). The data used in this model is arranged in a format of five-input parameters that cover the ordinary Portland cement (OPC) ratio, ground granulated blast furnace slag (GGBFS), fine aggregate ratio (Sand), water to binder (w/b) ratio, and superplasticizer (SP) ratio.

**Artificial Neural Network:**
An Artificial Neural Network is a collection of simple processing units or nodes that highly interconnected in different layers through links called connections (Dayhoff, 1990; Freeman and Skapura, 1991). The topology or architecture of ANNs may be presented schematically. The main tasks of processing units are to receive input from its neighboring units which provide incoming activations, compute an output, and send that output to its neighbors receiving its output. The strength of the connections among the processing units is provided by a set of weights which affect the magnitude of the inputs that will be received by the neighboring units. The output produced by the output processing units is compared to the target output data, and the weights are appropriately modified or adjusted based on a learning rule. ANN training algorithms are divided into two different groups which are supervised, and unsupervised (Dayhoff, 1990; Freeman and Skapura, 1991; Haykin, 1999). In this paper, with the aim of adjusting networks weights, based on difference between two values, including predict value and actual output; supervised learning algorithm have been used.

There are several types of ANNs such as Feed Forward NN, Hopfield NN, Self-Organizing NN and etc (Dayhoff, 1990; Freeman and Skapura, 1991; Fauselt, 1993). The most popular type is Feed Forward Backpropagation that consists of an input layer, one or more hidden layers and an output layer as shown in Figure 1.

![Fig. 1: Feed Forward Neural Network Topology](image)

Each node contains four main elements which are input, bias, activation function and output. The input of each node in hidden layer and output layer are values received from the preceding layer which is shown in Figure 2.
Where $X_i$ are inputs from the previous layer, $W_{ij}$ are weights of each connection for the input of node $i$ to node $j$, this values express the effect of an input set on the node, $b$ is the bias associated with node $j$ and $X_j$ is the net input. Another element of a neuron is activation function which shows the internal activation level and the other one is output ($Y$) which is generally obtained as a function of the net inputs. Eventually neural network which consists of a set of stable weights; have the ability to produce a perfect result by receiving the input and return the proper output.

**Fuzzy Inference System:**

Fuzzy Logic (FL) is an approximate reasoning method for coping with life’s uncertainties. Occasionally, the characteristics of various systems are very difficult to describe with mathematical equations because of their complexity (Zadeh, 1988; Serge, 2001; Wang, 1992). Unlike the two value logic, FL is a set of mathematical based on degrees of membership rather than on the crisp membership for knowledge representation. In the essence of FL, the notion of membership in a fuzzy set is a continuous value rather than a “yes” or “no” decision. Fuzzy set is a set with uncleared boundaries like tall, hot and etc where a function is being used to assign a value for each element to show the degree of their membership. Although there are several kinds of membership functions, typically the membership function used in the FL are triangles, trapezoids, and gaussians (Nayeripour, 2010; HanimahKamis, 2010). A continuous value between 0 and 1 provided by membership function is a measure for the likelihood that the instance will be in the set. Linguistic terms and numerical values may be defined by the characteristic functions as singletons, crisp sets and fuzzy sets. A linguistic variable is used to describe a concept with the vague value and conditional statement are used to capture the human knowledge known as fuzzy rules shown as below:

\[ \text{if } x \text{ is } A \text{ then } y \text{ is } B \]

where $x$ and $y$ are linguistic variables and $A$ and $B$ are linguistic values determined by fuzzy sets. These rules will be used in an inference system.

Fuzzy Inference System (FIS) is the process of formulating of mapping the given input to the output which includes four steps. These steps are input fuzzification, rule evaluation, aggregation of the rule outputs and defuzzification (PejmanTahmasebi, 2010; Akbarzadeh et al., 2009). In the input fuzzification step, crisp inputs is converted to the fuzzy values based on membership function. In the second step using the fuzzified input to find out the proper rules and its antecedents. The aggregation is the process of unification of the output of all rules. Finally the result of the FIS is converted to the crisp value in the defuzzification phase. There are two FIS that are Mamdani (Mamdani,1974; Mamdani and Assilian, 1975) and Sugeno (Takagi and Sugeno, 1985) which are varied somewhat in the way outputs are determined (PejmanTahmasebi, 2010; ZeyadAssiObaid et al., 2009).

**Neuro-Fuzzy System:**

Although FIS can solve many kinds of problems in the computational area, these systems are not able to adjust for better inference. Neuro-fuzzy system is such a system which has the ability to learn has been added to the FIS. This kind of system gives us the combination of computation and learning capabilities of ANN and the human knowledge representation of FL. While ANN are low-level computational structures that perform well dealing with raw data, FL deals with reasoning on a higher level, using linguistic information acquired from domain experts (By Robert Fullér (Book); a neuro-fuzzy approach for the classification of data, 1995; Neuro Fuzzy Systems: 2001; Kosko, 1996; Jang JSR, Sun, Mizutani E., 1997; Jang JSR, 1995).
The structure of neuro-fuzzy system looks like the multilayer ANN and it consists of input, output and three hidden layers. The three hidden layers are used to utilize the membership function and fuzzy rules in FIS. The input layer transmits the crisp input to the next layer then the number of neurons in this layer depends on the number of inputs of the system. The next layer is fuzzification layer that determines the membership value of each input in neuron's fuzzy sets. Moreover, the number of neurons are verified by the summation of fuzzy set for each input. Layer 3 is the fuzzy rule layer in which each neuron corresponds to single fuzzy rule that get the fuzzified input and find the rules where the input is in antecedents of the corresponding rule. In the next step which is called the output membership layer receives the input from corresponding fuzzy rules and combines them. The last layer the output is defuzzified and produces the desired crisp output (PejmanTahmasebi, 2010; Akbarzadeh, 2009). The Neuro-Fuzzy system is shown in Figure 3.

![Fig. 3: Neuro-Fuzzy System Structure](image)

**Architecture and Operations of the System:**

For the first step, the data which are used in the training and testing of neuro-fuzzy system have to be normalized. The purpose of this step is to avoid the numerical overflows due to very large or very small values. The normalization method in this paper is minmax function formulated as follows:

\[
\text{Normalized Value} = \frac{(\text{Input Value} - \text{Minimum Value})}{(\text{Maximum Value} - \text{Minimum Value})}
\]

This method limits the range of the input values into \([0,1]\) where data can be retrieved by the reverse method of the normalization.

The constructed neuro-fuzzy model consists of 5 layers as described above. The first layer has 5 neurons for 5 input vectors that are fuzzified using triangular fuzzy membership and each input are divided into 3 fuzzy sets. consequently the next layer contains 15 nodes for each fuzzy set.

**Casting Mortar for the Verification of the Developed Model:**

1 **Cement:**

Ordinary Portland Cement (OPC) was used during the study. The OPC used complied with the Type I Portland cement as in ASTM C150-05 (2005) and BS 12 (1991).

2 **Ground Granulated Blast Furnace Slag (GGBFS):**

The GGBFS used complied with the requirements in ASTM C989-05 (2005), which is equivalent to BS 6699 (1992).

3 **Find Aggregate (Sand):**

Locally available hill sand passing through 1.18 mm sieve (size No. 16) was used as fine aggregate in mortar for encasement. The sand used had the specifications of ASTM C778-02 (2002) and gradation was in accordance with the specifications of ASTM C33-03 (2003). The fineness modulus was found to be 2.36.
4 Superplasticizer (SP):

The superplasticizer was used as the chemical admixture during this study. It was type F high range water reducing admixture complying with ASTM C494-05a (2005). It was in dry powder form.

5 Water:

Water is one of the most important constituents without which concrete cannot be produced. It should not contain any substance, which can be harmful to the process of hydration of cement and durability of concrete. In this study tap water was used for the manufacture of the concrete.

RESULTS AND DISCUSSION

In order to optimize the network’s output and minimize the deviation, the normalization step is essential and the predicted values are denormalized to compare with the experimental values. The denormalized values for all test data sets can be observed in Table 2.

Neuro-Fuzzy Model and Parameters:

Five models of neuro-fuzzy were developed based on different sets of training and testing data and each model has five neurons as input layer and one neuron in the output layer. The next step is developing the models. The normalized dataset of 52 records, each containing five components for the input parameters and the one output value (compressive strength), was split in such a way that the parameters were divided into five data sets: set I, set II, set III, set IV and set V. For testing the reliability of the methodology, four data sets have been selected as a training set, and the remaining set was used to test the accuracy of the method. The method in this research is called five-cross validation method. Based on analysis results, Best model is the one with the highest value of $R^2$.

Experimental Data:

To develop an acceptable model, all patterns that are contained in the data need to be included in the training set. Similarly, the test set needs to be representative of the training set and should also contain all the patterns that are present in the available data. Hence, the data used for training and testing should represent almost the same population. Table 1 shows the statistical parameters of two sets of data. The statistical parameters include the mean, standard deviation, variance, minimum value and maximum value. The statistics of both training and testing sets are in great agreement meaning both represent almost the same population.

Table 1: Statistics of experimental data

<table>
<thead>
<tr>
<th></th>
<th>$f_{cu}$ (Mpa)</th>
<th>OPC (ratio)</th>
<th>GGBFS (ratio)</th>
<th>Sand (ratio)</th>
<th>Water (ratio)</th>
<th>SP (ratio)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Data</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No of Data</td>
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<td>41</td>
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<tr>
<td>Mean</td>
<td>41.33</td>
<td>0.65</td>
<td>0.34</td>
<td>2.50</td>
<td>0.62</td>
<td>0.26</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>8.91</td>
<td>0.27</td>
<td>0.28</td>
<td>0.44</td>
<td>0.10</td>
<td>0.18</td>
</tr>
<tr>
<td>Variance</td>
<td>79.54</td>
<td>0.08</td>
<td>0.08</td>
<td>0.20</td>
<td>0.10</td>
<td>0.03</td>
</tr>
<tr>
<td>Min Value</td>
<td>29.90</td>
<td>0.40</td>
<td>0.00</td>
<td>2.00</td>
<td>0.47</td>
<td>0.00</td>
</tr>
<tr>
<td>Max Value</td>
<td>54.00</td>
<td>1.00</td>
<td>0.60</td>
<td>3.00</td>
<td>0.79</td>
<td>0.50</td>
</tr>
<tr>
<td>Test Data</td>
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<td></td>
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<td></td>
<td></td>
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<td>No of Data</td>
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<td>11</td>
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<td>Mean</td>
<td>41.24</td>
<td>0.64</td>
<td>0.36</td>
<td>2.47</td>
<td>0.62</td>
<td>0.26</td>
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<tr>
<td>Std. Dev</td>
<td>8.03</td>
<td>0.27</td>
<td>0.27</td>
<td>0.40</td>
<td>0.09</td>
<td>0.17</td>
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<tr>
<td>Variance</td>
<td>64.46</td>
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<td>0.07</td>
<td>0.16</td>
<td>0.01</td>
<td>0.03</td>
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<td>0.00</td>
<td>2.00</td>
<td>0.47</td>
<td>0.00</td>
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<tr>
<td>Max Value</td>
<td>56.70</td>
<td>1.00</td>
<td>0.60</td>
<td>3.00</td>
<td>0.79</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Error analysis of Neuro-Fuzzy Models:

In order to achieve the best result we have implemented three models of 5 different pattern which finally the second model observed to be the optimized one with less error percent. In this model with the aim of reaching the least error and more accuracy 5 different pattern with different train and test data set have been developed. Referring to Figure 4(FIS6-T2 model (Data set II) with 1.79% error is the best model. Table 2 shows the test data sets in optimized algorithm for 5 different pattern.
**Fig. 4:** Error% comparison for different data sets in optimized algorithm

**Table 2:** Compressive strength for different data sets in optimized model

<table>
<thead>
<tr>
<th>Data Set I</th>
<th>Data Set II</th>
<th>Data Set III</th>
<th>Data Set IV</th>
<th>Data Set V</th>
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<td>Predict</td>
<td>Experiment</td>
<td>Predict</td>
<td>Experiment</td>
<td>Predict</td>
</tr>
<tr>
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<td>45.30</td>
<td>44.46</td>
<td>43.00</td>
<td>49.22</td>
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<td>33.29</td>
<td>33.60</td>
<td>52.68</td>
<td>54.00</td>
<td>36.02</td>
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<tr>
<td>42.16</td>
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<td>43.22</td>
<td>42.50</td>
<td>38.95</td>
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<tr>
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<td>31.14</td>
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<td>39.07</td>
<td>43.20</td>
<td>36.88</td>
<td>37.00</td>
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<td>53.38</td>
<td>52.00</td>
<td>51.43</td>
<td>51.80</td>
<td>33.02</td>
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<tr>
<td>41.80</td>
<td>40.70</td>
<td>40.18</td>
<td>40.40</td>
<td>40.85</td>
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<tr>
<td>-</td>
<td>-</td>
<td>30.59</td>
<td>29.90</td>
<td>31.71</td>
</tr>
</tbody>
</table>

**Model Predictions:**

Figure 5. shows the performance of the predictions of the FIS6-T2 model for both training and testing data. The Pearson coefficients for linearity between experimental and predicted values are 0.9889 and 0.9638 for the test and training data, respectively, which is almost equal to 1.0 and it shows that there is very high correlation between predict values and experimental values.

The histogram showing the differences of predicted and experimental values for testing data is shown in Figure 6. About 73% predictions of FNN model lie within the 2.5% error. There are a few number of results that have more than 2.5% out of the range error.
Table 3 with all the input details is also included for the optimized model, the differences between predicted values and experimental values are also given in terms of percent. In this study, the value of the binder is assumed to 1.0, therefore the w/b ratio depend on the water content only and fine aggregate ratio depend on the sand content only since whatever value divided by one is equal the same to the that value which are mentioned in the Table 3.

Table 3: Comparison of experimental and FNN predicted values of compressive strength

<table>
<thead>
<tr>
<th>OPC (ratio)</th>
<th>GGBFS (ratio)</th>
<th>Sand (ratio)</th>
<th>Water (ratio)</th>
<th>SP (ratio)</th>
<th>Experimental $f_{cu}(Mpa)$</th>
<th>Predicted $f_{cu}(Mpa)$</th>
<th>Differential %</th>
</tr>
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<tr>
<td>1.0</td>
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<td>0.0</td>
<td>44.46</td>
<td>43.00</td>
<td>0.03386</td>
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<td>1.0</td>
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<td>2.0</td>
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<td>0.5</td>
<td>52.68</td>
<td>54.00</td>
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<td>0.4</td>
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<td>0.4</td>
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<tr>
<td>0.4</td>
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<td>2.5</td>
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<tr>
<td>0.4</td>
<td>0.6</td>
<td>3.0</td>
<td>0.73</td>
<td>0.2</td>
<td>30.59</td>
<td>29.90</td>
<td>0.02292</td>
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Conclusion:

This paper demonstrates the capabilities and advantages of using Fuzzy Neural Networks in modeling and prediction of the Compressive Strength of Slag-Cement Based Mortars. It is clear that FNNs have an advantage over the traditional regression analysis. Unlike in regression analysis, no functional relationship among the variables is assumed before we can develop an FNNs model. FNNs automatically construct the relationships and adapt based on the training data presented. The more appropriate data in training and testing sets, the better result and prediction. The average deviation of predicted values by FNN model is just about 0.018% of the existing experimental values.

The study also illustrates the capabilities and advantages of using FNNs in modeling physical processes. Unlike in regression analysis, before we can develop an FNN model no functional relationship among the variables is assumed. FNNs automatically construct the relationships and adapt based on the training data presented to them. The study also shows the importance of validating the performance of FNN models in simulating physical processes especially when data are insufficient. Furthermore, the proposed fuzzy neural network model will save time, reduce waste material and decrease the design cost. Regarding to this facts FNNs have strong potential as a feasible tool for predicting compressive strength of mortar.

REFERENCES


“Introduction to neuro-fuzzy systems” By Robert Fullér (Book).


Zain, M.F.M. and S.M. Abd; “Multiple Regression Model for Compressive Strength Prediction of High Performance Concrete”.

