

# Hybrid Feed – Forward Back Propagation Neural Network Model: A Sensitivity Analysis of Corypha Utan Lam Fiber and Surkhi with Levenberg – Marquardt and Connection Weights Algorithm on a Fuzzy Inference System

Dante L. Silva<sup>1</sup>, Kevin Lawrence M. de Jesus<sup>2</sup>, Bernard S. Villaverde<sup>3</sup>

<sup>1,2,3</sup> School of Civil, Environmental and Geological Engineering, Mapua University

## Article Info

Volume 83

Page Number: 4868 - 4873

Publication Issue:

March - April 2020

## Abstract

A current advancement in the concrete technology includes its ability to improve the mechanical properties significantly thru the utilization of fiber reinforced concrete. Due to the upsurge in the construction activities, the demand for the construction materials increase which can cause detrimental effects in the environment. Sustainability is one of the key issues that is needed to be addressed in the construction industry. Surkhi and Buntal Fiber was utilized as an alternative material in concrete production. Artificial Neural Network was utilized to obtain the best model for predicting compressive ( $f_c$ ) and flexural strength ( $f_b$ ). Upon adopting Levenberg – Marquardt Algorithm and Hyperbolic tangent sigmoid as the training and transfer function, respectively, the final topology of the best model is 2-6-2 (Input Neuron-Hidden Neuron-Output Neuron). The weights produced from these model was utilized to determine the relative importance of Surkhi (S) and Buntal Fiber (BF) in compressive and flexural strength using Connection Weights (CW) algorithm. Based on the results of CW algorithm, the importance ranking for compressive strength is  $BF < S$  while for flexural strength is  $S < BF$ . Parametric analysis was also performed as part of the sensitivity analysis to observe the behavior of the  $f_c$  and  $f_b$  upon employing varying amounts of surkhi and buntal fiber. The use of these artificial intelligence tools is in line with the transition to industry 4.0 and an essential tool for applying sustainability in the construction industry.

## Article History

Article Received: 24 July 2019

Revised: 12 September 2019

Accepted: 15 February 2020

Publication: 27 March 2020

**Index Terms:** Sensitivity Analysis, Connection Weights Algorithm, Neural Network, Surkhi, Buntal Fiber

## I. INTRODUCTION

Fast development and growth instigated an abrupt thriving in the construction industry in the Philippines. The upsurge in infrastructure projects ends in larger requirement in production of different construction materials which has a detrimental effect in the environment. Many waste materials have been used in the construction example of these materials are, sawdust, steel slags, fly ash, volcanic ash, etc. [1]. Sustainability is one of the key issues in

construction due to the vast demand for materials as it is a worldwide booming industry. Fine aggregates were one of the most commonly utilized material in construction industry. The huge volume of usage of this material might result to a possible shortage in the near future therefore researches and studies regarding potential alternatives should be done. Materials such as Surkhi and Buri (Corypha Utan Lam) fiber was utilized to determine its performance and sustainability in concrete – based structures.

Various studies were performed determining the relationship of Surkhi and Buntal Fiber to the  $f_c$  and  $f_b$  of concrete. The utilization of Surkhi as a replacement to sand has a positive impact in the compressive capacity of a concrete brick sample [1]. Another study concluded that full replacement of Surkhi by weight of sand presents enhanced compressive strength in contrast to samples produced with sand [2]. Furthermore, the utilization of fan palm fiber increases the flexural strength of concrete which resulted to an increase of flexural strength between 10% to 20% [3].

Artificial intelligence has developed a great number of tools to decipher the most challenging problems in science. Soft computing methods are frequently modeled on processes that derive in nature such as brain or natural selection. These methods allow for unclear, inexact and ambiguous data [4]. Several studies were completed that utilizes Artificial Neural Network (ANN) which is under the family of Artificial Intelligence Models. Models on predicting high strength concrete, self – compacting, lightweight, fiber reinforced and admixtures were completed using ANN [5]. Another study utilized ANN for predicting  $f_c$  and  $f_b$  of concrete using polypropylene fibers [6]. Additionally, a study employed a hybrid approach associating ANN and Genetic Algorithms (GA) to optimize the fresh and mechanical characteristics of self – compacting concrete [7].

Sensitivity Analysis determines, quantifies and describe the significance of each independent variable to the dependent variable. Numerous approaches can be employed in performing sensitivity analysis such as Connection Weights (CW) algorithm which is employed to establish the relative importance of the input factors to the desired output and determines the sum of the products of the weights from the layers of the network [8]. Parametric Analysis which is utilized to describe the behavior of the required output upon having varying values of the input parameters [9]

and Fuzzy Inference Systems (FIS) through the use fuzzy set theory to manage the inaccuracy and ambiguity that is essential to the human decision in judgment formulating procedures through the employment of syntactical terms and degrees of membership [10].

In this study, varying percentages of fibers with increments of 0.25% were added to the concrete ranging from 0% to 1.5%. Likewise, varying percentage of sand replaced with surkhi ranging from 0% to 30% were utilized. These data were used to create samples and determine its compressive and flexural strength. The data sets comprising the surkhi, buntal fiber, compressive and flexural strength were utilized to perform neural network simulation to obtained the best predicting model and perform the sensitivity analysis through the use of the weights and biases generated from the simulation.

The purpose of the research is to observe and attain the behavior, relative importance and surface models of the surkhi and buntal fiber relative to the compressive and flexural strength using artificial neural network and coupling it with connection weights algorithm, parametric analysis and fuzzy inference system.

## II. METHODOLOGY

### A. Experimental Program

In this phase, testing methods from ACI and ASTM were followed for the development of the testing program and experimental design. Sixty (60) samples were created using varying percentages of Surkhi (S) and Buntal Fibers (BF). These samples were subjected to compressive (30 samples) and flexural strength test (30 samples).

### B. Neural Network Model Simulation

A multi – objective model was developed to forecast the compressive and flexural strength using the percentage of surkhi and buntal fibers. This study utilized the back propagation algorithm which is the

most commonly used type of Artificial Neural Network. For the amount of hidden layers and neurons of ANN, there are no particular rule and it involves numerous trial and error procedures until an adequate value is achieved [11].

The multilayer feed – forward neural network comprises computational neurons which were arranged to individual hidden and output layers. The association concerning two neurons is termed as the connection weights. Every node includes a transfer function which is essential to determine the neuron’s added input to its output. Additionally, the bias is a supplementary neuron factor that is added up together with the weighted inputs of the neuron [12]. The governing design of the f’c and fb model is presented in figure 1.

The stopping criteria used is the Pearson’s Correlation Coefficient ( $R_{all}$ ), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). These values are statistical measurement factors employed to compute the connection and the variance concerning computed and forecasted quantities, respectively. Equations for computing the Mean Squared Error, Pearson’s Correlation Coefficient and Mean Absolute Percentage Error are as presented below:

$$MSE = \frac{1}{n} \sum_{i=1}^n (x_i - p_i)^2 \quad (1)$$

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x}_i)(p_i - \bar{p}_i)}{\sqrt{\sum_{i=1}^n (x_i - \bar{x}_i)^2 \sum_{i=1}^n (p_i - \bar{p}_i)^2}} \quad (2)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|\hat{y}_t - y_t|}{y_t} \times 100 \quad (3)$$

where  $x_i$  is the actual value,  $\bar{x}_i$  is the average of targeted actual value,  $p_i$  is the network predicted yield,  $\bar{p}_i$  is the average of network predicted yield,  $\hat{y}_t$  is the quantity predicted by the model for variable t,  $y_t$  is the quantity attained for variable t and n is the number of data sets.

### C. Sensitivity Analysis

For the sensitivity analysis, three methods were performed to describe and determine the behavior and relative importance of the surkhi and buntal fiber to the f’c and fb of the concrete sample: connection weights algorithm, parametric analysis, and fuzzy inference system.

For the connection weights algorithm, the weights from the input to the hidden layer and as well as the weights from the hidden to the output layer was utilized to establish the relative importance in terms of percentage of surkhi and buntal fibers to the f’c and fb of concrete. For the parametric analysis, the governing model from the simulation was utilized to describe graphically the trend and behavior of compressive and flexural strength upon using varying amounts of surkhi and buntal fiber. Lastly, for the fuzzy inference system, the association concerning the input and output factors was created utilizing surface modelling technique.

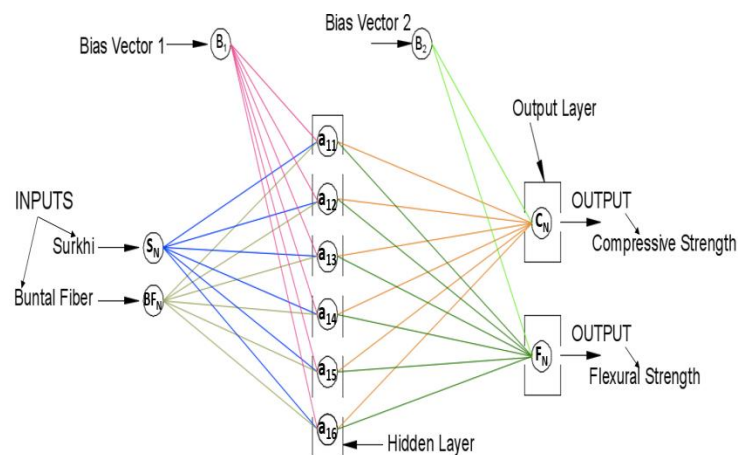


Figure 1. ANN Architecture for f’c and fb Model

## III. RESULTS AND DISCUSSION

### A. Experimental Program

Upon curing the samples for 28 days, it was subjected for compressive and flexural strength tests. Table 1 presents the description of the testing results for the samples which was utilized in the simulation using Artificial Neural Network.

**Table 1. Details of the Experimental Design**

	Maximum	Minimum
Surkhi	30%	0%
Buntal Fiber	1.5%	0%
Compressive Strength	19.33 MPa	8.81 MPa
Flexural Strength	4.20 MPa	1.55 MPa

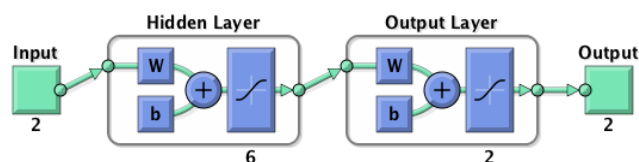
Note: Percentages by weight were utilized for both Surkhi and Buntal Fibers

### B. Neural Network Model Simulation

Series of simulations were performed to determine the best model for predicting compressive ( $f_c$ ) and flexural strength ( $f_b$ ) using surkhi and buntal fibers. It was found out that Levenberg – Marquardt algorithm is the best training algorithm, tansig as the best transfer function and six (6) is the best number of hidden neurons. The best model was selected utilizing the following stopping criteria: highest Pearson’s Correlation Coefficient ( $R_{all}$ ), lowest MSE, and lowest MAPE.

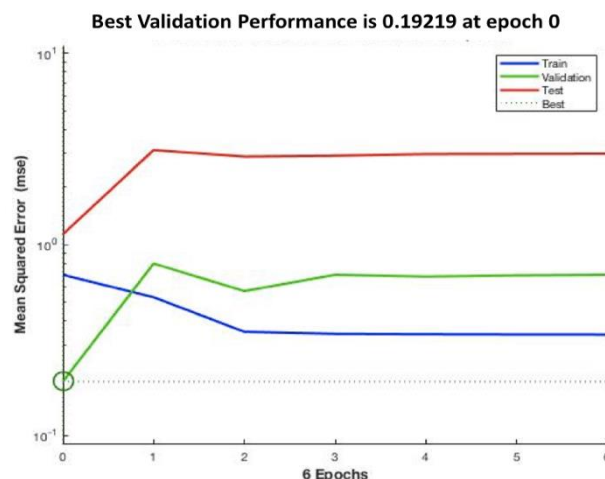
**Table 2. Simulation Results for the Best Model**

Training Algorithm	Transfer Function	No. of HN	Training	Validation
Levenberg-Marquardt	tansig	6	0.98925	0.99615
Testing	All	MSE	MAPE $f_c$	MAPE $f_b$
0.97638	0.9884	0.19219	7.013%	7.792%

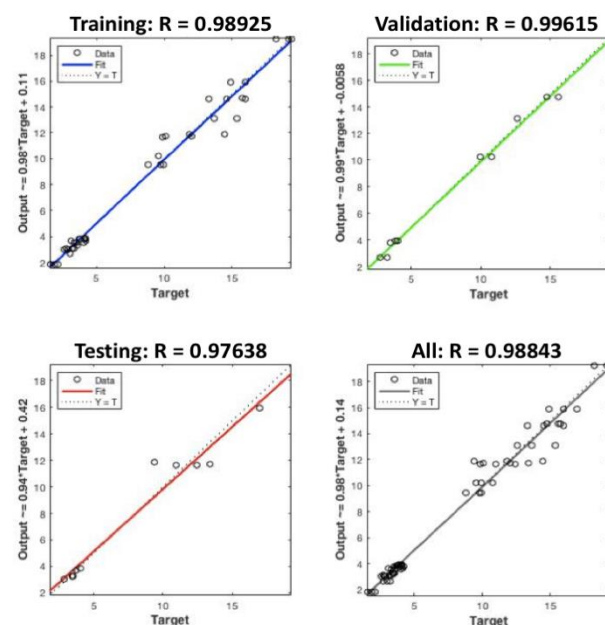


**Figure 2. Overview of the Architecture of the Governing Model**

The performance and the regression plots of the governing model were presented in figure 3 and 4. The best performance was at MSE equal to 0.19219 and the highest Rall value of 0.98843.



**Figure 3. Performance of the Governing Model**



**Figure 4. Regression Plots of the Governing Model**

### C. Sensitivity Analysis

The relative importance of surkhi and buntal fiber to the compressive and flexural strength was calculated using the connection weights algorithm.

**Table 3. Connection Weights Products, Relative Importance and Rank of Inputs to Compressive Strength**

Node	Hidden 1	Hidden 2	Hidden 3
Surkhi	2.253	6.219	2.483
Buntal Fiber	0.952	2.456	5.025
Node	Hidden 4	Hidden 5	Hidden 6

Surkhi	0.984	4.299	2.737
Buntal Fiber	1.163	3.136	1.143
<b>Node</b>	<b>Sum</b>	<b>Relative Importance</b>	<b>Rank</b>
Surkhi	18.975	57.762%	1
Buntal Fiber	13.875	42.238%	2

**Table 4. Connection Weights Products, Relative Importance and Rank of Inputs to Flexural Strength**

<b>Node</b>	<b>Hidden 1</b>	<b>Hidden 2</b>	<b>Hidden 3</b>
Surkhi	0.903	0.202	1.559
Buntal Fiber	2.138	0.511	0.770
<b>Node</b>	<b>Hidden 4</b>	<b>Hidden 5</b>	<b>Hidden 6</b>
Surkhi	1.804	0.722	0.843
Buntal Fiber	1.527	0.990	2.018
<b>Node</b>	<b>Sum</b>	<b>Relative Importance</b>	<b>Rank</b>
Surkhi	6.034	43.133%	2
Buntal Fiber	7.955	56.867%	1

The relative importance (RI) of surkhi and buntal fiber to compressive and flexural strength were presented in table 3 and table 4. Using connection weights algorithm, it was determined that for compressive strength surkhi is the more influential factor with RI of 57.762% while for the flexural strength buntal fiber is the more influential factor with RI of 56.867%.

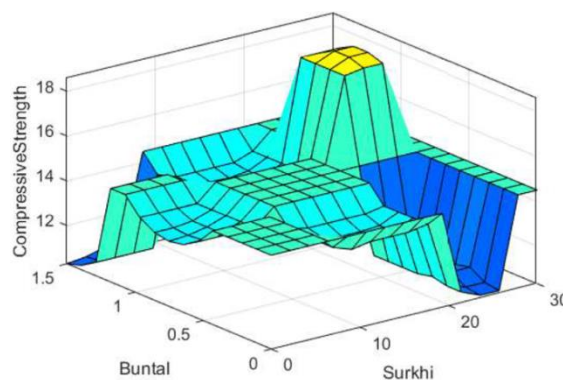
For the parametric analysis, considering the effect of varying amounts of buntal fiber to compressive ( $f_c$ ) and flexural strength (fb), the highest compressive strength was obtained upon having 0.75% of buntal fiber in the sample after which the compressive strength have a decreasing value. On the other hand, the least flexural strength was obtained using 0.75% buntal fiber then the flexural strength increases afterwards. The behavior of the  $f_c$  and fb was displayed in figure 5.

As observed for the compressive ( $f_c$ ) and flexural strength (fb) behavior using variable amounts of buntal fiber, the highest compressive strength was attained upon using 21% buntal fiber while the least flexural strength was attained using 12% buntal

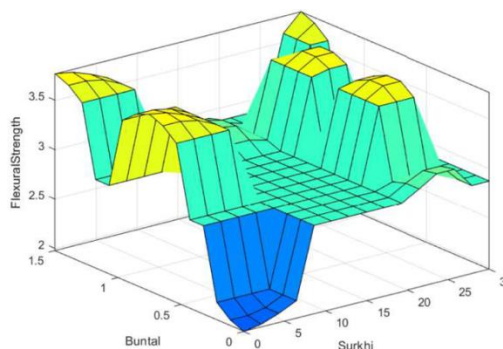
fiber. The behavior of the  $f_c$  and fb was presented in figure 6.

Two input parameters were employed for Mamdani's Fuzzy System modeling – Surkhi and Buntal fiber as displayed in Figure 7 and 8. Only triangular membership functions were used for every variable in the study for simplicity. In generating simulations utilizing fuzzy control surface modeling, the graphical results showed the two input variables (i.e, surkhi and buntal fiber) values denoted as x- and z-axis while the output parameter (i.e. compressive and flexural strength) represented the y-axis.

To investigate the fuzzy control surface, the blue areas are the lowest points, the light blue areas are the combinations which are weaker in strength compared to the conventional concrete mix, the green areas show a surge in  $f_c$  and fb and the yellow areas are the highest points of the data.



**Figure 7. Fuzzy Control Surface Modeling of Compressive Strength**



**Figure 8. Fuzzy Control Surface Modeling of Flexural Strength**

## CONCLUSION

The use of Artificial Intelligence tools is a capable tool for predicting and determining the relative importance of factors considering a target output. Upon completing the simulations performed in the study using the connection weights algorithm, it was therefore concluded that surkhi was the more influential factor in the compressive strength of concrete sample while the buntal fiber was the more important factor for the flexural strength of concrete sample. Moreover, the behavior of the compressive and flexural strength was observed upon using varying amounts of surkhi and buntal fiber. The final importance ranking for compressive strength is  $BF < S$  while for the flexural strength is  $S < BF$ . The use of sensitivity analysis techniques gave a new dimension in analyzing the effect of parameters on a target output.

## REFERENCES

- [1] Wani. "Influence of Surkhi on Various Properties of Concrete Bricks," International Journal of Engineering Research & Technology (IJERT), Vol. 6(04), 1201–1209, 2017.
- [2] Kushwaha and L. Padu. The Study of Compressive Strength on Concrete by Using Surkhi, 5(Xi), 374–377, 2017
- [3] M. Machaka, A. Elkordi, and H. Abou Chakra. ALKALI TREATMENT OF FAN PALM NATURAL FIBERS FOR USE IN FIBER REINFORCED CONCRETE Hisham Basha. European scientific journal. 1010. 1857-7881, 2014
- [4] G.W. Flintsch and C. Chen. "Soft Computing Applications in Infrastructure Management," Journal of Infrastructure Systems, Volume 10(4), 157-166.
- [5] H. Eskandari-Naddaf and R. Kazemi. "ANN prediction of cement mortar compressive strength, influence of cement strength class," Construction of Building Materials, 138, 1-11, 2017
- [6] S. J. C. Clemente, E. C. D. Alimorong, and N. C. Concha. "Back Propagation Artificial Neural Network Modeling of Flexural and Compressive Strength of Concrete Reinforced with Polypropylene Fibers," International Journal of Geomate, 16(57), 183-188, 2019.
- [7] N. C. Concha and E. Dadios. "Optimization of the rheological properties of self-compacting concrete using neural network and genetic algorithm," In 2015 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 1-6, 2015.
- [8] J. D. Olden, and D. A. Jackson. "Illuminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks," Ecological modelling, 154(1-2), 135-150, 2002.
- [9] M. M. Rashidi, N. Galanis, F. Nazari, A. Basiri Parsa and L. Shamekhi. "Parametric Analysis and Optimization of Regenerative Clausius and Organic Rankine Cycles with Two Feedwater Heaters using Artificial Bees Colony and Artificial Neural Network," Energy, 36(2011), 5728 – 5740, 2011.
- [10] A. Amindoust, S. Ahmed, A. Saghafinia and A. Bahreininejad. "Sustainable supplier selection: A ranking model based on fuzzy inference system," Applied Soft Computing, 12(2012), 1668 – 1677, 2012.
- [11] G. H. Kim, S. H. An, and K. I. Kang. "Comparison of construction cost estimating models based on regression analysis, neural networks, and case – based reasoning," Building and Environment, Vol. 39, 1235 – 1242, 2004.
- [12] G. Heravi and E. Eslamdoost. "Applying Artificial Neural Networks for Measuring and Predicting Construction – Labor Productivity," Journal of Construction Engineering and Management, 04015032, 2015.