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Research Article

Application of an artificial neural network for predicting compressive and flexural strength of basalt fiber added lightweight

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ABSTRACT

Concrete is known as one of the fundamental materials in construction with its high amount of use. Lightweight concrete (LWC) can be a good alternative in reducing the environmental effect of concrete by decreasing the self-weight and dimensions of the structure. In order to reduce self-weight of concrete artificial aggregates, some of which are produced from waste materials, are utilized, and it also contributes to develop a sustainable material Artificial neural networks have been the focus of many scholars for long time with the purpose of analyzing and predicting the lightweight concrete compressive and flexural strengths. The artificial neural network is more powerful method in terms of providing explanation and prediction in engineering studies. It is proved that the error rate of ANN is smaller than regression method. Furthermore, ANN has superior performance over nonlinear regression model. In this paper, an ANN based system is proposed in order to provide a better understanding of basalt fiber reinforced lightweight concrete. In the regression analysis predicted vs. experimental flexural strength, R-sqr is determined to be 86%. The most important strength contributing factors were analyzed within the scope of this study.

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1. Introduction

Concrete is known for its high standard of use as one of the essential building materials. It is widely used in buildings, hydraulic structures, and pavements (Calis and Yıldızel, 2019). Due to its high consumption, the normal weight aggregates (NWAs), such as granite and gravel, in construction concrete, natural stone deposits have decreased dramatically. Such amount of use caused non-recoverable damages to the natural environment in the past and goes on. Consequently, the need for sustainable materials has become apparent in recent years (Alengaram et al., 2013).

Lightweight concrete (LWC) can be a good alternative in reducing the environmental effect of concrete by decreasing self-weight and dimensions of the structure. To reduce self-weight of concrete artificial aggregates, some of which are produced from waste materials, are utilized, and it also contributes to developing a sustainable material (Zi et al., 2014). LWC is defined as a versatile material, and it received great attention from the whole construction industry in recent years. LWC can be also utilized as structural concrete, which makes it important material in the modern construction industry. In this respect LWC has been able to solve durability and weight problems in many building and exposed structures (Jafari and Mahini, 2017). Oven dry density of LWC is at the range of 300-2000 kg/m^3 and compressive strength of a cube is from 1 to 60 MPa (Hamad, 2017).

Strength of LWC is as important as it is for conventional concrete. Hence, LWC is required to meet specific strength requirements which can be different depending upon the project. To increase properties of LWC, fibers are commonly used by the scholars. Influences of fiber on mechanical properties of LWC has been investigated by the researchers (Alengaram et al., 2017; Lv et al., 2015; Zhou and Brooks, 2019). These fibers can be mainly divided in to 3 main type: metallic, synthetic and

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natural. Carbon, glass, steel, rubber, waste cable steel and glass are widely used fibers. Among others steel fibers (SF) are mostly used to increase the compressive strength of both normal and lightweight concrete (Wu et al., 2019). Recent studies report that compressive strength can be increased by adding SF. Furthermore, flexural strength and splitting tensile increase significantly (Alengaram et al., 2017; Libre et al., 2011). LWC is known with its low shear capacity in comparison to normal weight concrete. Fiber addition can develop this weak property of LWC. The impact of steel fibers on LWC shear behaviour has been reviewed and concluded that; 0.5% SF addition increased shear resistance from 50.7 kN to 76.6 kN which is 51%. Similarly, when SF addition is 1.0%, the shear resistance enhanced 68% (Mo et al., 2017).

There is limited number of researches on the utilization of glass fiber in LWC. However, it is reported that LWC, which contains 0.06% glass fiber, show 7-11% higher compressive strength than 0% glass fiber added LWC (Hamad, 2017). The compressive strength difference increases by higher level of GF addition. Similarly, another study shows that with GF usage of 0.00 to 0.06%, the compressive strength increases remarkably from 57.85 MPa to 66.01 MPa (Hilles and Ziara, 2019). Also, it is determined that when the amount of GF is higher than 0.06%, the increase of compressive strength is insignificant. Splitting tensile, on the other hand, has increase trend with the increase of GF from 0.00% up to 1.2%. The increase on splitting tensile is higher than compressive strength.

Researchers (Fashandi et al., 2018) investigated the effect of carpet wastes in LWC. It was observed that compressive strength reduces 5.39 %, 8.49% and 14.76% with the use of carpet waste with 1%, 2% and 3%. Flexural strength shows similar trend with the compressive strength. Change in dry density determined to be from 4% up to 14%. Therefore, utilization of carpet wastes has negative impact on both compressive and flexural strength of the concrete. Water absorption of carpet waste added samples is at the range of 6.8% and 9.3%. Obviously, water absorption of concrete is due to high porosity of carpet wastes and this leads the increment.

The Abrams' water-to-cement (binder) ratio (w/c) formula is world-wide accepted by the scholars. The concept of the Abrams' formula indicates that when w/c ratio decreases the strength of concrete increases, when w/c increases strength decreases. This approach does not consider the other ingredients that can impact concrete strength though (Yeh, 1998). It was proved that other ingredients such as silica fume and fiber additions have also impacts on concrete specimen strength (Bhanja and Sengupta, 2005). The current empirical equations compute compressive strength (CS) by investigating the test results without considering supplementary cementitious materials. However, the impact of these supplementary materials such as fibers, fly ash, basalt furnace on compressive strength should also be reviewed (Bhanja and Sengupta, 2005; Yildizel and Calis, 2019). Concrete properties are also influenced by other parameters: quality and quantity of aggregate, cement type (Chopra et al., 2019) .In order to get better understanding regarding the nature of the concrete and optimise the concrete design, concrete composition should be investigated in deep (Castelli et al., 2013). Fiber distribution in concrete mixtures makes difficult to understand and predict compressive strength of concrete mixtures (Altun et al., 2008). Traditional approaches used to determine effect of the parameters on concrete mechanical properties based on analytical equation which fails to get a deep view of it (Getahun et al., 2018). Therefore, the need for generating better solution has grown. In this study basalt fiber added lightweight concrete compressive and flexural strength is investigated by modelling artificial neural networks.

Neural networks have been employed in various fields including structural and engineering problems (Altun et al., 2008). These networks aim to model human brain and perform some of its actions. Neural networks (NN) originally come from mathematical neurobiology. NN are beneficial in predicting and classifying problems. In fact, for these types of problems regression models or some other statistical techniques are also used (Paliwal and Kumar, 2009). NN was investigated in terms of statistical aspects and classified as type of flexible nonlinear regression method. NN is capable of recognizing patters from the past data when it is properly structured and trained (Lenard et al., 1995). Multiple regression, discriminant analysis and logistics regression are the traditional techniques that widely used in prediction and classification problems. NN have gained importance in the recent years, and consequently become alternative solution to the traditional methods in prediction and classification problems (Ripley, 1994).

Artificial neural networks can be considered as purely data driven model that through training iteratively transition from a random state to a final model (Smith and Mason, 1997). Even combination of various algorithms can be used via NN (Behnood and Golafshani, 2018; Yan and Lin, 2016; Yildizel et al., 2020). The recent study reviewed some features of cost estimation model namely; stability, ease and performance in a car manufacturing industry. These features have been investigated by using regression analysis method and neural networks. According to the results, NN have certain benefits in handling data which do not comply with general low order polynomial forms or, which do not have the appropriate cost estimation relationships (CER) for regression modeling with data for which a prior is not very knowledgeable. When sufficient cost estimation relationship data is available, regression models are significantly advanced in predicting (Smith and Mason, 1997). In the other study (Lee et al., 2005), the relationship between welding parameters and geometry of the backbead in arc welding was investigated. Numerous ANN's along with regression analysis methods were utilized in order to perform prediction of the relationship. It was concluded that the error rate predicted by ANN is smaller than the prediction of multiple regression analysis. Scholars concluded that ANN is more powerful in terms of providing explanation and prediction. Furthermore, ANN easily explores the relationships between the data that cannot be understood by the traditional methods (Dvir et al., 2006). In other study, the factors that have impact on the object-oriented (OO) component size

and source code documentation was questioned. Author reviewed the performance of both nonlinear artificial neural networks predicting model and linear regression model. According to the results obtained in the study, when variable returns to scale economies exist between multiple inputs and multiple outputs, ANN has superior performance over nonlinear regression model (Pendharkar, 2006).

Researchers utilized artificial neural networks to understand hybrid steel systems (Allahyari et al., 2018). In their study 90 records was reviewed. The data classified under 2 classes namely training and test. The "train" dataset which has 76 out of 90 records, is utilized in updating the network weight and biases, and computing the gradient. The error of test dataset is not used in the training process, and yet it is still useful to compare different models (Lee and Lee, 2014).

ANN and genetic algorithm in risk optimization of supply chain management were also investigated (Nezamoddini et al., 2019). In that study a typical supply chain structure that contains; supplier, manufacturing plant, distribution center and end user/market was reviewed, and genetic learning algorithm and ANN was used. Nonlinear chance-constrained model in which the uncertainties in center disruption, demand, transaction times, capacity failure, price were taken in to account. The objective function was to maximize net profit by minimizing the initial costs and increasing the market demand.

GEP is an advanced algorithm which includes the idea that the single linear chrome is of a fixed length used in genetic algorithms as well as the structure of the tree, in various sizes and shapes, used for genetic programming. GEP can be considered as a new subarea of GP, which basically contains function set, fitness function, control parameters, terminal set, and termination condition. The main difference between GP and GEP is the way solution is represented in (Jafari and Mahini, 2017).

In other study it was (Tanyildizi and Cevik, 2010) aimed to get empirical genetic programming formulas to predict both compressive and splitting strength of lightweight concrete contains silica and exposed to high temperature. The formulas have been produced by training sets. In their study, properties of genes and functions such as length, number, type of lining, have been selected for each problem. During the solution process, the user is able to start with a single-gene chromosome and then in the later stage this can be increased (Tanyildizi and Cevik, 2010).

A new structured was developed to for prediction of TBM jamming risk in squeezing ground by using Bayesian and ANN (Hasanpour et al., 2019). As part of neural network transaction method if any error occurs in the training this goes backward. This is called backpropagation which is mainly useful in minimizing errors.

Sahar and others (Mohammadi and Nazemi, 2020) studied in management area and analyzed a whole portfolio of projects in terms of value, uncertainty of returns and value by using ANN. Zhang established a model to asses investment risks (Zhang, 2020) and other studies reviewed the prediction of compressive strength of concrete (Duan et al., 2013; Getahun et al., 2018), the other study investigates predicting of lightweight foamed concrete by using ANN (Yaseen et al., 2018).

This study aims to analyze flexural and compressive strength of basalt fiber added lightweight concrete containing ground calcium. In the laboratory part various concrete specimens were tested. The obtained data from the laboratory tests were computed in ANN. In this study 170 samples were prepared, and 17 number of various mixture design were prepared and tested in the laboratory.

2. Materials and Method

2.1. Materials

In the experimental study fine aggregate (FA), also known as river sand, Pumice Aggregates (PA), Betocarb (GCC) and CEM I 42.5 R Cement were utilized. The particle size distributions of the combined aggregates can be seen in Fig. 1.

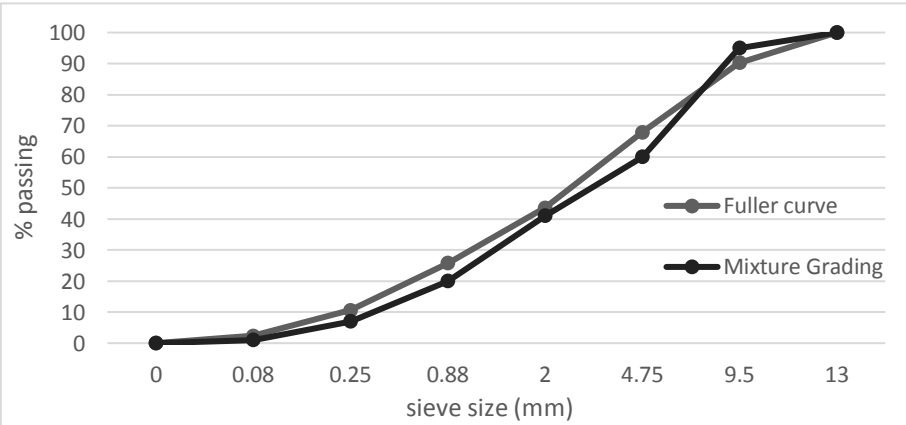

Fig. 1. Fuller curve and aggregate gradation.

Physical properties of the used aggregates (pumice aggregate PA, fine aggregate FA) and the fibers (basalt fiber BF) are shown in Tables 1 and 2. 6mm length BF was used with the volume of 0.25%, 0.5%, 0.75% and 1% in the experimental study. Physical properties of betocarb (GCC) is shown in the Table 3. Polycarboxylic type hyper plasticizer was included in all mixtures at the rate of 1.25 % of cement by weight.

Table 1. Properties of fiber.

Aggregates/property	FA	PA
Particle size (mm)	0- 4	2-12
Particle density (g/cm³)	2.73	2.21

Table 2. Material properties of BFs.

Technical property	
Elasticity module, MPa	90
Tensile strength, MPa	4832
Melting point, °C	1452
Application temperature, °C	-220/+980
Chemical composition	**Percentages (%)**
SiO_2	51.2-58.9
Al_2O_3	14.5-18.2
Fe_2O_3	5.7-9.6
MgO	3.0-5.4
$FeO + Fe_2O_3$	9.2-14.0
TiO_2	0.8-2.25
$Na_2O + K_2O$	0.8-2.25
Others	0.08-0.14

Table 3. Physical properties and chemical compositions of cement, PA and Betocarb® (GCC).

Material property	Cement	PA	Betocarb® (GCC)
Fe_2O_3, %	3.52	1.5	
CaO, %	60.21	0.2	
SiO_2, %	20.19	75.84	
MgO, %	2.32	0.4	
SO_3, %	2.61	0.5	
Al_2O_3, %	4.32	12.54	
Free CaO, %	1.7	-	
Loss on ignition	2.85	5.63	
Specific gravity	3.12	2.35	
Specific surface (cm²/g)	3,618	-	>30,000
Blue value	-	-	<3
d50%	-	-	3

Compressive strength tests were performed on the Ø100/100 mm cylindrical specimens according to ASTM C469 standard. Flexural strength tests were conducted with 100 x 100 x 500 mm prismatic samples according to the EN 14651. The specimens for flexural strength (FS) were prepared 100 x 100 x 500 samples then cut into 5 pieces to carry out flexural strength tests. The sample can be seen in Fig. 3.

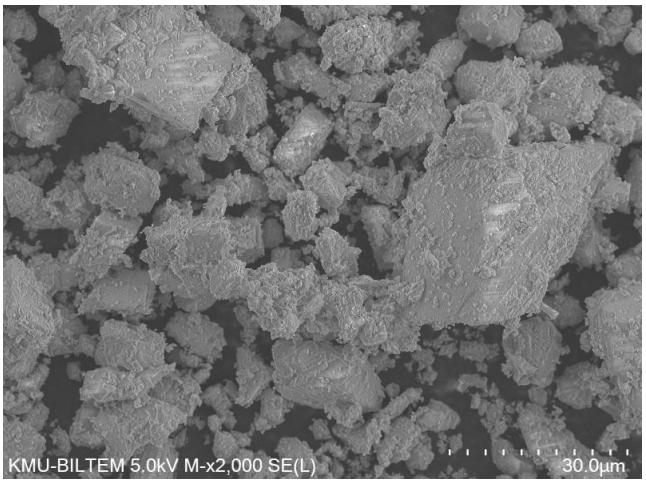

Fig. 2. SEM photo of lightweight concrete.

Fig. 3. Lightweight concrete sample.

2.2. Neural network

In the neural networks 5 variables namely; grounded calcium carbonate (GCC), basalt fiber (BF), Cement (C), fine aggregate (FA), pumice aggregate (PA) are utilized as utilized as input while compressive strength (CS) and flexural strength (FS) are used targets in separate neural networks. Neural network structure is shown in the Fig. 4. The neural network consists of; a scaling layer, a neural network and unscaling layer. The green circles represent scaling neurons, the blue one's perceptron neurons and the orange one unscaling layers. Input values were selected based on the previous experimental test result (Yildizel and Calis, 2019). Levenberg-Marquardt approach were used in this study. This method was designed to reach second - order training speed without having to determine the Hessian matrix (Gavin, 2013). Optimization algorithm is given in Table 6.

The scaling method for this layer is selected by the neural network. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation. Table 4 represents scaling layer and can be seen below.

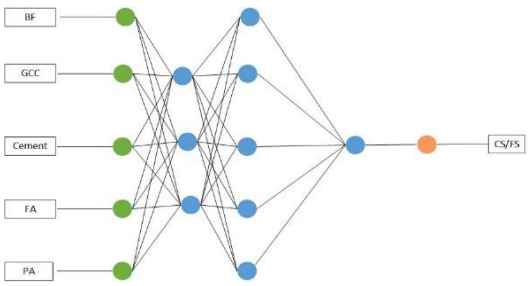

Fig. 4. Neural network.

The size of the unscaling layer is 1, the number of outputs. The un-scaling method for this layer is the minimum and maximum. The following table shows the values which are used for scaling the inputs, which include the minimum, maximum, mean and standard deviation. Data classification of ANN was carried out as proposed: 80% of the data for training and 20% for testing. Unscaling layer can be seen in Table 5.

Basic statistics are very valuable information when designing a model, as they may alert the presence of spurious data. It is necessary to check the correctness of the most important statistical measures of each variable. Table 7 shows the minimums, maximums, means and standard deviations of all the variables in the data set. The scaling layer size is 5, which is the number of inputs.

The norm of the parameters gives a clue as to the accuracy of the predictive model. If the standard parameters are small, the model will be smooth. On the other hand, if the standard parameters are very high, the model may become unstable. Also, it can be noted that the norm depends on the number of parameters. Proposed parameters norms were obtained as 4.19 and 4.24 for compressive and flexural strengths respectively.

Table 4. Scaling layer.

	Minimum	Maximum	Mean	Deviation
BF	0	1	0.588	0.318
GCC	0	25.5	12	9.98
Cement	145	170	158	9.99
FA	741	891	812	58.8
PA	40	450	358	101

Table 5. Unscaling layer.

Minimum	Maximum	Mean	Deviation
14.2	16.7	15.4	0.629

Table 6. Optimization algorithm.

Factors	Description	Value
Damping parameter factor	Damping parameter increase/decrease factor.	10
Minimum parameters increment norm	Norm of the parameters increment vector at which training stops.	0.001
Minimum loss decrease	Minimum loss improvement between two successive epochs.	1e-12
Loss goal	Goal value for the loss.	1e-12
Gradient norm goal	Goal value for the norm of the objective function gradient.	0.001
Maximum selection error increases	Maximum number of epochs at which the selection error increases.	100
Maximum iterations number	Maximum number of epochs to perform the training.	1000
Maximum time	Maximum training time.	3600

Table 7. Data set distribution.

	Minimum	Maximum	Mean	Deviation
BF	0	1	0.59	0.32
GCC	0	25.50	12.01	9.98
Cement	144.50	170	158	9.99
FA	741	891	811.59	58.79
PA	40	450	358.24	100.76
CS	14.21	16.69	15.39	0.63
FS	0.98	1.55	1.32	0.20

3. Results and Discussion

The compressive strength of lightweight concrete is vitally important as it is for conventional concrete. In addition to the environmental effects the ingredients of concrete namely: aggregate, cement, water to cement ratio, existence of fiber, chemical additions, and cement replacement materials. Cement replacement material such as GCC, fly ash perform as filler material and reduce the porosity of concrete. Consequently, the inclusion of such material increases compressive strength (Yildizel and Calis, 2019). In this study it is also proven that GCC has significantly positive impact on the compressive strength of lightweight concrete. It is determined that the optimum amount of GCC is 17 kg for compressive strength as presented in Fig. 6. Cement amount and water to cement (w/c) ratios are another significant factor that impacts the mechanical and durability properties of lightweight concrete. Furthermore, fiber inclusion is another important factor over mechanical properties. Especially, the flexural strength of concrete can be increased by adding basalt fiber as it improves bonding strength.

Regression charts are shown in Fig. 5. R-sqr values were obtained as 84.2% and 86% for estimated compressive and flexural strength respectively, compared to the experimental test results. According to the presented results it is clear that the proposed, ANN model has a good classification and analysing capacity.

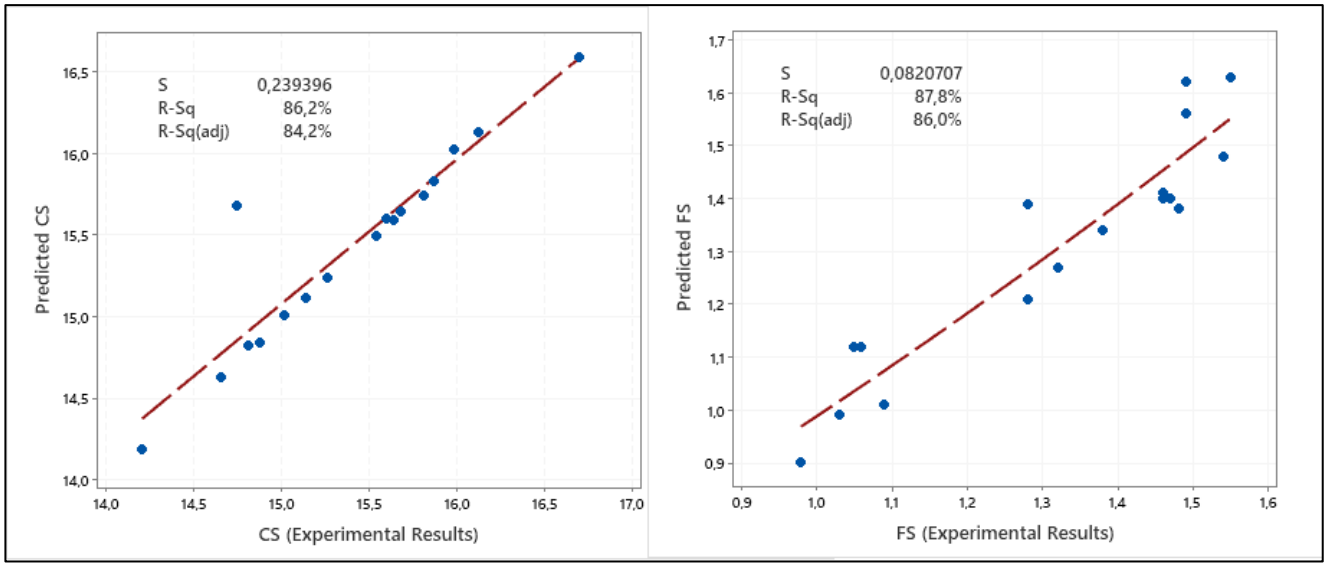

Fig. 5. Experimental results vs. predicted compressive strength (CS) and flexural strength (FS).

Main effects plot for FS and CS are shown in Fig. 6. Samples containing cement content substituted by more than 10 per cent showed lower performance compared to other mixtures. BFs inclusions increased the flexural test results. Mechanical performance improvement of samples can be related to the filler effect of the addition of ground calcium carbonate and basalt fiber to the sample flexural behaviors.

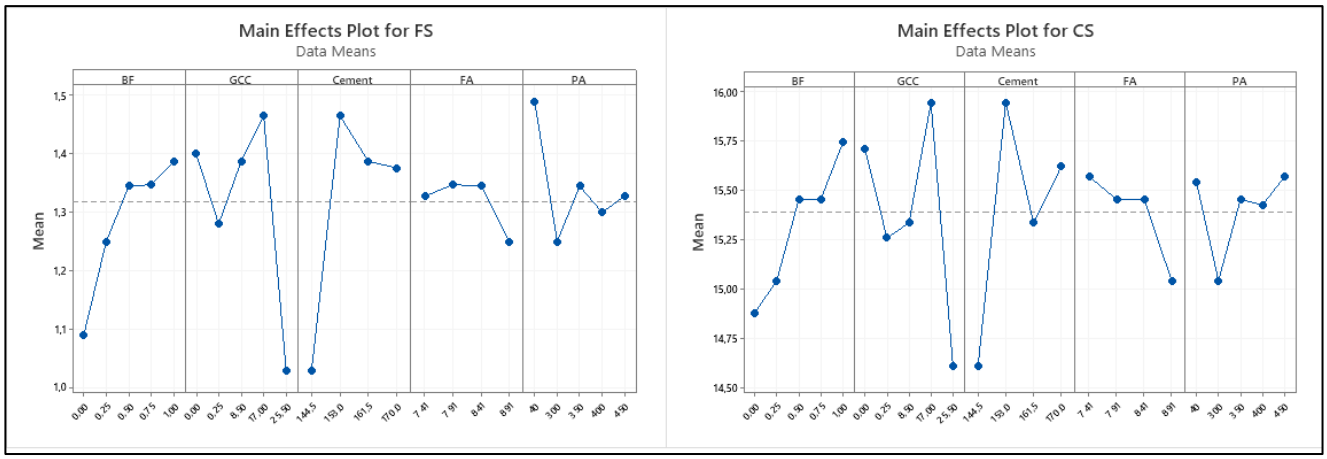

Fig. 6. Main effects plot for FS and CS.

The mathematical expression represented by the neural network is shown in the appendix below. The inputs BF, GCC, Cement, FA, PA are used to compute the output FS. The information is used in propagation in a feed-forward fashion through scaling layer, the perceptron layers and the unscaling layer.

4. Conclusions

The purpose of this study is to develop an ANN based system in order to provide a better understanding for basalt fiber reinforced lightweight concrete. The most important strength contributing factors were analyzed in this research. The outcomes of the research can be drawn as follows:

- As proved earlier by the scholars, the ANN model also approves the strong correlation between the predicted flexural and compressive strengths and experimental test results. In this study, the R-sqr is quite dependable with the value of 84% and 86%.
- Further studies can be carried out with the obtained mathematical equation and applied to the other properties of lightweight concrete.
- The study outcomes can be assessed by other artificial and mathematical systems for improving better ANN-

based systems. More efficient R-sqr values can be obtained by implications of other ANN based systems, which consequently improves the quality of prediction structure.

- Future actions can include the application of the presented methodology to other concrete technologies using the model with new correlation coefficients for estimating.

Appendix

scaled_BF = 2*(BF-0)/(1-0)-1;

scaled_GCC = (GCC-12.0147)/9.97515;

scaled_Cement = 2*(Cement-144.5)/(170-144.5)-1;

scaled_FA = (FA-811.588)/58.7868;

scaled_PA = (PA-358.235)/100.762;

y_1_1 = tanh (0.0152537+ (scaled_BF*-0.912022)+ (scaled_GCC*-2.50899)+ (scaled_Cement*1.40554)+ (scaled_FA*-0.997674)+ (scaled_PA*-2.3887));

y_1_2 = tanh (-0.178526+ (scaled_BF*1.28838)+ (scaled_GCC*-1.46236)+ (scaled_Cement*-0.472198)+ (scaled_Pa*0.54,089));

y_1_3 = tanh (2.18567 + (scaled_BF*1.55428)+ (scaled_GCC*0.130318)+(scaled_Cement*0.566491)+ (scaled_FA*-1.3308)+(scaled_PA*0.492229));

y_2_1 = tanh (-1.40062+ (y_1_1*1.064444)+ (y_1_2*-1.30571)+ (y_1_3*0.467421));

y_2_2 = tanh(-0.367843+ (y_1_1*-1.65566)+ (y_1_2*2.37658)+ (y_1_3*-0.916468));

y_2_3 = tanh (1.80226+ (y_1_1*0.18265)+ (y_1_2*0.10069)+ (y_1_3*-0.916468));

scaled_FS = (-0.181899+ (y_2_1*1.56442)+ (y_2_2*1.60345)+ (y_2_3*1.72238));

FS = (0.5*(scaled_FS+1.0)*(1.55-0.98)+0.98);

References

Allahyari HM, Nikbin I, Rahimi RS, Heidarpour A (2018). A new approach to determine strength of Perfobond rib shear connector in steel-concrete composite structures by employing neural network. *Engineering Structures*, 15, 235–249.

Alengaram UJ, Ghazali NB, Jumaat MZ, Yusoff S, Bashar I, Islam A (2017). Influence of steel fibers on the mechanical properties and impact resistance of lightweight geopolymer concrete. *Construction and Building Materials*, 152, 964–977.

Altun F, Kişi Ö, Aydin K (2008). Predicting the compressive strength of steel fiber added lightweight concrete using neural network. *Computational Materials Science*, 42(2), 259–265.

Behnood A, Golafshani EM (2018). Predicting the compressive strength of silica fume concrete using hybrid artificial neural network with multi-objective grey wolves. *Journal of Cleaner Production*, 202, 54–64.

Bhanja S, Sengupta B (2005). Influence of silica fume on the tensile strength of concrete. *Cement and Concrete Research*, 35(4), 743–747.

Calis G, Yıldızel SA (2019). Investigation of roller compacted concrete: Literature review. *Challenge Journal of Concrete Research Letters*, 10(3), 63–74.

Castelli M, Vanneschi L, Silva S (2013). Prediction of high performance concrete strength using Genetic Programming with geometric semantic genetic operators. *Expert Systems with Applications*, 40(17), 6856–6862.

Chopra P, Sharma RK, Kumar M (2019). Prediction of compressive strength of high-volume fly ash concrete using artificial neural network. *Advances in Materials Science and Engineering*, 25, 471–483.

Duan ZH, Kou SC, Poon CS (2013). Prediction of compressive strength of recycled aggregate concrete using artificial neural networks. *Construction and Building Materials*, 40, 1200–1206.

Dvir D, Ben-David A, Sadeh A, Shenhar AJ (2006). Critical managerial factors affecting defense projects success: A comparison between neural network and regression analysis. *Engineering Applications of Artificial Intelligence*, 19(5), 535–543.

Gavin HP (2013). The Levenberg-Marquardt method for nonlinear least squares curve-fitting problems. *Department of Civil and Environmental Engineering Proceedings,* Duke University, NC, USA.

Getahun MA, Shitote SM, Abiero-Gariy ZC (2018). Artificial neural network based modelling approach for strength prediction of concrete incorporating agricultural and construction wastes. *Construction and Building Materials*, 190, 517–525.

Hamad AJ (2017). Size and shape effect of specimen on the compressive strength of HPLWFC reinforced with glass fibers. *Journal of King Saud University - Engineering Sciences*, 29(4), 373–380.

Hasanpour R, Rostami J, Schmitt J, Ozcelik Y, Sohrabian B (2019). Prediction of TBM jamming risk in squeezing grounds using Bayesian and artificial neural networks. *Journal of Rock Mechanics and Geotechnical Engineering*, 12(1), 21–31.

Hilles MM, Ziara MM (2019). Mechanical behavior of high strength concrete reinforced with glass fiber. *Engineering Science and Technology, an International Journal*, 22(3), 920–928.

Jafari S, Mahini SS (2017). Lightweight concrete design using gene expression programing. *Construction and Building Materials*, 139, 93–100.

Lee K, Booth D, Alam P (2005). A comparison of supervised and unsupervised neural networks in predicting bankruptcy of Korean firms. *Expert Systems with Applications*, 29(1), 1–16.

Lee S, Lee C (2014). Prediction of shear strength of FRP-reinforced concrete flexural members without stirrups using artificial neural networks. *Engineering Structures*, 61, 99–112.

Lenard MJ, Alam P, Madey GR (1995). The Application of Neural Networks and a Qualitative Response Model to the Auditor's Going Concern Uncertainty Decision. *Decision Sciences*, 26(2), 209–227.

Libre NA, Shekarchi M, Mahoutian M, Soroushian P (2011). Mechanical properties of hybrid fiber reinforced lightweight aggregate concrete made with natural pumice. *Construction and Building Materials*, 25(5), 2458–2464.

Lv J, Zhou T, Du Q, Wu H (2015). Effects of rubber particles on mechanical properties of lightweight aggregate concrete. *Construction and Building Materials*, 91, 145–149.

Mo KH, Yeoh KH, Bashar II, Alengaram UJ, Jumaat MZ (2017). Shear behaviour and mechanical properties of steel fiber-reinforced cement-based and geopolymer oil palm shell lightweight aggregate concrete. *Construction and Building Materials*, 148, 369–375.

Mohammadi S, Nazemi A (2020). On portfolio management with value at risk and uncertain returns via an artificial neural network scheme. *Cognitive Systems Research*, 59, 247–263.

Mollahasani A, Alavi AH, Gandomi AH (2011). Empirical modeling of plate load test moduli of soil via gene expression programming. *Computers and Geotechnics*, 38(2), 281–286.

Nezamoddini N, Gholami A, Aqlan F (2020). A risk-based optimization framework for integrated supply chains using genetic algorithm and artificial neural networks. *International Journal of Production Economics*, 3, 110–122,

Paliwal M, Kumar UA (2009). Neural networks and statistical techniques: A review of applications. *Expert Systems with Applications*, 36(1), 2–17.

Pendharkar PC (2006). Scale economies and production function estimation for object-oriented software component and source code documentation size. *European Journal of Operational Research*, 172(3), 1040–1050.

Ripley BD (1994). Neural networks and related methods for classification. *Royal Statistical Society*, 56(3), 409–456.

Smith A, Mason AK (1997). Cost estimation predictive modeling: Regression versus neural network. *Engineering Economist*, 42(2), 137–161.

Tanyildizi H, Çevik A (2010). Modeling mechanical performance of lightweight concrete containing silica fume exposed to high temperature using genetic programming. *Construction and Building Materials*, 24(12), 2612–2618.

Wu T, Yang X, Wei H, Liu X (2019). Mechanical properties and microstructure of lightweight aggregate concrete with and without fibers. *Construction and Building Materials*, 199, 526–539.

Yan F, Lin Z (2016). New strategy for anchorage reliability assessment of GFRP bars to concrete using hybrid artificial neural network with genetic algorithm. *Composites Part B: Engineering*, 92, 420–433.

Yaseen ZM, Deo RC, Hilal A, Abd AM, Bueno LC, Salcedo-Sanz S, Nehdi ML (2018). Predicting compressive strength of lightweight foamed concrete using extreme learning machine model. *Advances in Engineering Software*, 115(3), 112–125.

Yeh IC (1998). Modeling of strength of high-performance concrete using artificial neural networks. *Cement and Concrete Research*, 28(12), 1797–1808.

Yildizel SA, Calis G (2019). Design and optimization of basalt fiber added lightweight pumice concrete using Taguchi Method. *Revista Romana de Materiale/Romanian Journal of Materials*, 49(4), 544–553.

Yildizel SA, Tayeh BA, Calis G (2020). Experimental and modelling study of mixture design optimisation of glass fiber-reinforced concrete with combined utilisation of Taguchi and Extreme Vertices Design Techniques. *Journal of Materials Research and Technology*, 9(2), 2093–2106.

Zhang J (2020). Investment risk model based on intelligent fuzzy neural network and VAR. *Journal of Computational and Applied Mathematics*, 371, 112-125.

Zhou H, Brooks AL (2019). Thermal and mechanical properties of structural lightweight concrete containing lightweight aggregates and fly-ash cenospheres. *Construction and Building Materials*, 198, 512–526.

Zi G, Kim S, Choi J, Hino S,Yamaguchi K (2014). Influence of fiber reinforcement on strength and toughness of all-lightweight concrete. *Construction and Building Materials*, 69, 381–389.