8th Jordan International Civil Engineering Conference on
Smart Civil Engineering
27-29 Sep 2022, Amman-Jordan

PREDICTING THE PROPERTIES OF HIGH-PERFORMANCE CONCRETE USING ARTIFICIAL INTELLIGENCE

Omar Shamayleh*, Harry Far

School of Civil and Environmental Engineering Faculty of Engineering and Information Technology, University of Technology Sydney (UTS), 15 Broadway, Ultimo, NSW 2007 (PO Box 123), Australia

Keywords: concrete, artificial neural networks, geopolymer concrete, high-performance concrete, supplementary cementitious material

Abstract. The most popular building material, concrete, is intrinsically linked to the advancement of humanity. Due to the ever-increasing complexity of cementitious systems, concrete formulation for desired qualities remains a difficult undertaking despite conceptual and methodological advancement in the field of concrete science. Recognising the significant pollution caused by the traditional cement industry, construction of civil engineering structures has been carried out successfully using Geopolymer Concrete (GPC), also known as High Performance Concrete (HPC). These are concretes formed by the reaction of inorganic materials with a high content of Silicon and Aluminium (Pozzolans) with alkalis to achieve cementitious properties. These supplementary cementitious materials include Blast Furnace Slag, a waste material generated in the steel manufacturing industry; Fly Ash, which is a fine waste product produced by coal-fired power stations and Silica Fume, a by-product of producing silicon metal or ferrosilicon alloys. This result demonstrated that GPC/HPC can be utilised as a substitute for traditional Portland cement-based concrete, resulting in improvements in concrete properties in addition to environmental and economic benefits. This study explores utilising experimental data to train artificial neural networks, which are then used to determine the effect of supplementary cementitious material replacement, namely fly ash, granulated blast furnace slag and silica fume, on the compressive strength, tensile strength, and modulus of elasticity of concrete and to predict these values accordingly. †

* Corresponding author: PhD candidate in School of Civil and Environmental Engineering, Faculty of Engineering and Information Technology, University of Technology Sydney (UTS), e-mail: omar.a.shamayleh@student.uts.edu.au

1. INTRODUCTION

Concretes incorporating Supplementary Cementitious Materials are referred to in the literature as Geopolymers (Davidovits 1991). Utilising SCMs correspondingly reduces the energy requirement of manufacturing cement and concrete, thus incurring further cost savings. Moreover, Supplementary Cementitious Materials are typically industrial waste materials which, if not utilised, would end up in landfills or man-made ponds where their contents are liable to leach into surface and ground water, causing extensive pollution and health hazards.

Geoploymer Concrete (GPC) has been found to have higher compressive strength than comparable concretes utilising ordinary Portland cement (Deb, Nath & Sarker 2015). Highlighting these enhanced properties, the phrase "high-performance concrete" (HPC) has emerged as synonym for GPC in the construction sector. In addition to the Portland cement, fine and coarse aggregates, and water that make up traditional concrete, additional cementitious elements including fly ash and blast furnace slag as well as chemical admixtures like superplasticizer are required for the production of HPC. Modelling the behaviour of high-performance concrete is a challenging endeavour due to the material's extreme complexity (Yeh 1998).

Concrete mix design is a complex and important subject that necessitates expert knowledge of the consistent materials and challenges related to their use. Constructing a useful end-product, a building or bridge for example, is contingent on availability of concrete with the necessary strength and other utility qualities. Concrete hardening and hydration are irreversible processes. Therefore, any mistakes in the concrete mix design are quite expensive for the investor, both during construction and after the structure has been used due to reduced durability (Ziolkowski & Niedostatkiewicz 2019).

Facing these challenges, artificial intelligence (AI) is increasingly utilised in concrete research as a complementary approach, and is providing new perspectives and useful solutions for accelerating innovations in the design and development of cementitious materials. The intrinsic complexity of concrete mixtures and their attributes can be taken into account by (AI) by utilising current datasets with data-driven models, which can automatically learn implicit patterns. An experiment series employing that material is used to train a neural network, which is the fundamental approach to creating a brain-based model for material behavior. The trained neural network will have enough knowledge of the material's behaviour to qualify as a material model if the experimental findings contain the pertinent information about the material's behavior. Such a trained neural network should be able to approximate the outcomes of other trials in addition to being able to replicate the experimental findings it was trained on (Ghaboussi, Garrett & Wu 1991).

Machine learning and Artificial Neural Networks (ANN) have been employed in numerous studies to determine and predict the mechanical properties of concrete. Yeh (1998) prepared several batches of high performance concrete which showed satisfactory experimental results, and subsequently utilised the data to train an artificial neural network, concluding “The strength model based on the artificial neural network is more accurate than the model based on regression analysis”. Chou et al. (2014) used advanced machine learning (ML) techniques to predict concrete compressive strength, concluding that their results confirm the suitability of ML methods for quick and effective concrete compressive strength computations. Boğa, Öztürk & Topçu (2013) developed a four-layered artificial neural network method (ANN) and determined that the ANN model can estimate experimental data to a remarkably close degree.

This study investigates the potential of utilising artificial neural networks (ANN) to determine the effect of replacement of ordinary Portland cement with supplementary cementitious materials (HPC), notable fly ash, granulated blast furnace slag and silica fume, on the mechanical properties of hardened concrete, including compressive strength and modulus of elasticity. The main advantages of using a neural network approach are that all of a material's behaviour can be represented in a single, cohesive environment provided by a neural network, and the neural network-based model is created directly from experimental data using the neural network's learning capabilities. This paper will not discuss in detail the artificial neural network methodology because it has been covered in numerous papers and books. Section 2 of the following sections provides an explanation of the artificial neural network. The network used to predict the compressive strength of concrete is examined in Section 3. The model is examined in Section 4 along with a number of proportioning factors in order to track the HPC's strength behaviour. To validate the suggested strategy, experiments are used in Section 5. Section 6 provides results and conclusions.

2. ARCHITECTURE OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are a class of massively parallel architecture that function in conjunction with highly networked artificial neurons to tackle complex problems. The vast majority of research utilises back-propagation neural networks (McClelland, Rumelhart & Group 1987). The network is trained by altering the link weights in accordance with the knowledge it has gained through training. By comparing each input pattern's goal output with the network's output for that pattern, the network learns by computing the error and propagating an error function backward through the network. After the network has been trained, it is given values for the project's input parameters in order to run. Following that, the network computes the node outputs using the weight values and thresholds already in place from the training phase. Because the system only needs to generate the network node values once, executing the network happens very quickly (Zupan 1994).

To test the accuracy of a trained network, the Root Mean Square Error (RMSE) is adopted, which commonly used method for comparing values predicted by a model or estimate to values observed in a sample or population. It gauges how well the proposed model can predict and replicate patterns in the experimental data in order to forecast the outcome (Hyndman & Koehler 2006).

3. MODELLING OF STRENGTH OF HIGH-PERFORMANCE CONCRETE

Learning Algorithm

The Levenberg-Marquardt method has been used as the learning algorithm to train the ANN model. The Gauss-Newton and Gradient Descent functions are both used by this approach to access the best run-by-run performance. While gradient descent uses the idea of absolute minima and absolute maxima, Gauss-Newton uses MSE as the cost function; the criterion which quantifies how good a model is (Sheskin 2004). The absolute maximum is the highest value on a cost function graph, whereas absolute minimum is the lowest point on the graph. Because it makes use of both the Gradient Decent and the cost function, the Levenberg-Marquardt algorithm performs better than other algorithms (Bafitlhile, Li & Li 2018). Since this algorithm gets the optimal value more quickly than other algorithms, it requires less training time. Many software programs employ this approach for curve fitting or regression.

The number of neurons in the Hidden Layer is deterimed as follows. The number of hidden layer neurons are 2/3 (or 70% to 90%) of the size of the input layer. If this is insufficient then number of output layer neurons can be added later on (Boger & Guterman 1997). The number of hidden layer neurons should be less than twice of the number of neurons in input layer (Berry & Linoff 2011). With these considerations in mind, the cost function was optimised to determine the number of neurons in the hidden layer. The performance of the cost function was recorded for each iteration of the program, which was repeated a number of times. It was decided to choose the number of neurons that predicted the output with the highest correlation.

With these considerations in mind, the cost function was optimized to determine the number of neurons in the hidden layer. The performance of the cost function was recorded for each iteration of the program, which was repeated a number of times. It was decided to choose the number of neurons that predicted the output with the highest correlation.

How the ANN code functions

The first step is Importing the data set from the directory. Subsequently, pre-processing of the data (Correlation, Null Values, filling Missing) is carried out, followed by distinguishing of input and output variables. Once this has been completed, data is split for training, validation, and testing in proportions of 80%, 10%, and 10%, respectively. Model construction is then carried out utilising 10 neurons. RMSE is then calculated for every output, and the actual and anticipated values are used to produce the regression plot. This is followed by optimizing the quantity of neurons to produce the best correlation between experimental and predicted values. Optimisation allows for selecting the ideal number of neurons and reinforcing the model. Finally, the regression plots are replotted and the RMSE recalculated. The steps above are illustrated in the following flow chart.

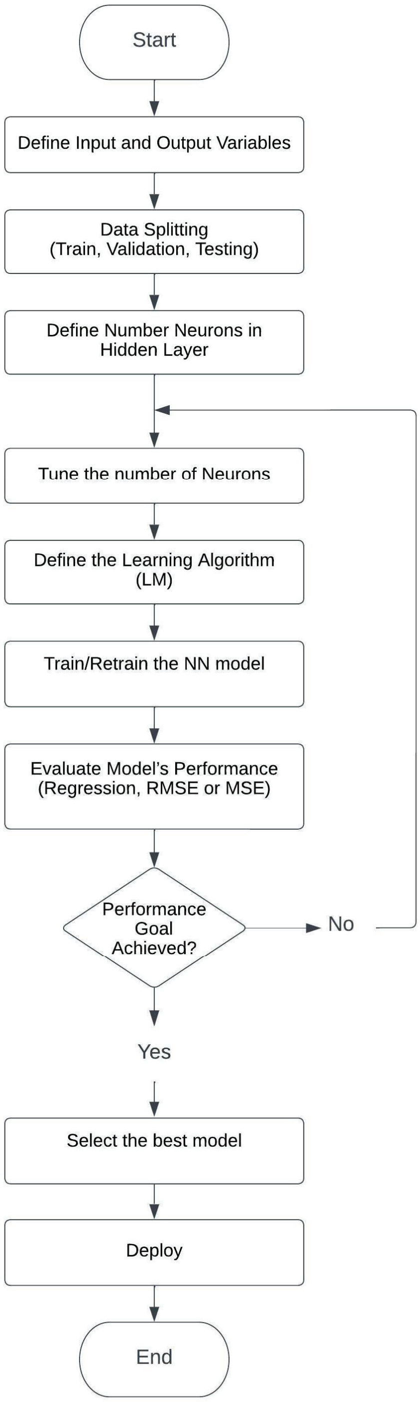

Figure 1 Modelling methodology flowchart for this study

4. DATA SETS AND EXPERIMENTAL DATA (TRAINING ANN)

This study uses date obtained from the National Research and Development Project, known as New RC Project, supported by the Ministry of Construction and the Research Committee on High-strength Concrete of the Architectural Institute of Japan (Tomosawa & Noguchi 1995). More than 3,000 data points on the correlation between compressive strengths and modulus of elasticity were gathered and statistically analysed (Tomosawa & Noguchi 1995). These data points were gathered by numerous researchers using a variety of materials. The examined concretes' compressive strengths ranged from 20 to 160 MPa. This data is used to train the developed artificial neural network developed for this study, such that by varying the factors of fly ash content, GGBS content and silica fume content, predictions for the value of compressive strength, modulus of elasticity and tensile strength can be obtained.

5. TRAINING RESULTS

As stated in the earlier explanation of the ANN code and shown in Figure 1, splitting for training, validation, and testing in proportions of 80%, 10%, and 10%, respectively had been carried out. The training results can be summarised as follows

Compressive Strength

Initially the model was trained with 10 number of neurons in the hidden layer, and the predications for compressive strength obtained and compared to experimental results. The performance of the model can be observed in the following regression plots.

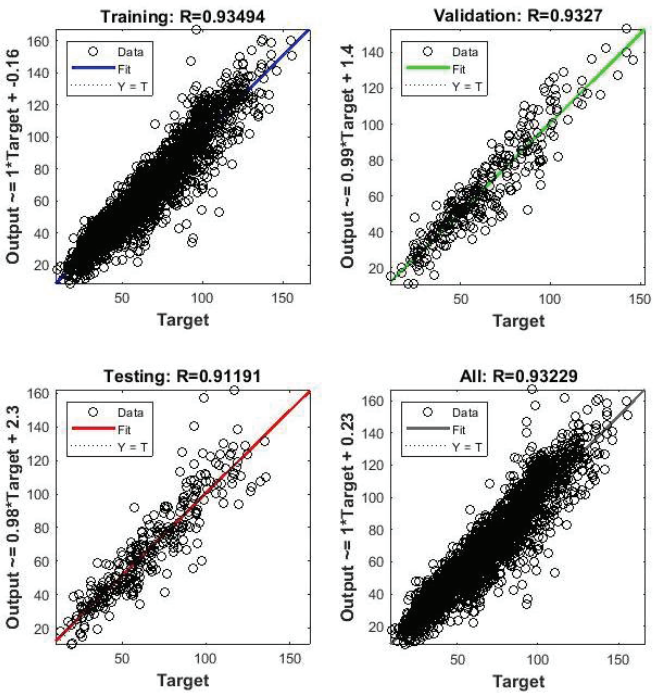

Figure 2: Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples.

Figure 2 shows the comparison between the predicted compressive strength and the actual values reported in the experimental results in (Tomosawa & Noguchi 1995). The sample correlation coefficient (r) measures how closely the points on a scatter plot are related to a linear regression line constructed using those points, with a value close to 1 indicating a strong correlation. Performance of the model is acceptable for training but may be improved in the case of testing, therefore an attempt is made to optimise the number of neurons. Figure 3 shows the optimisation process.

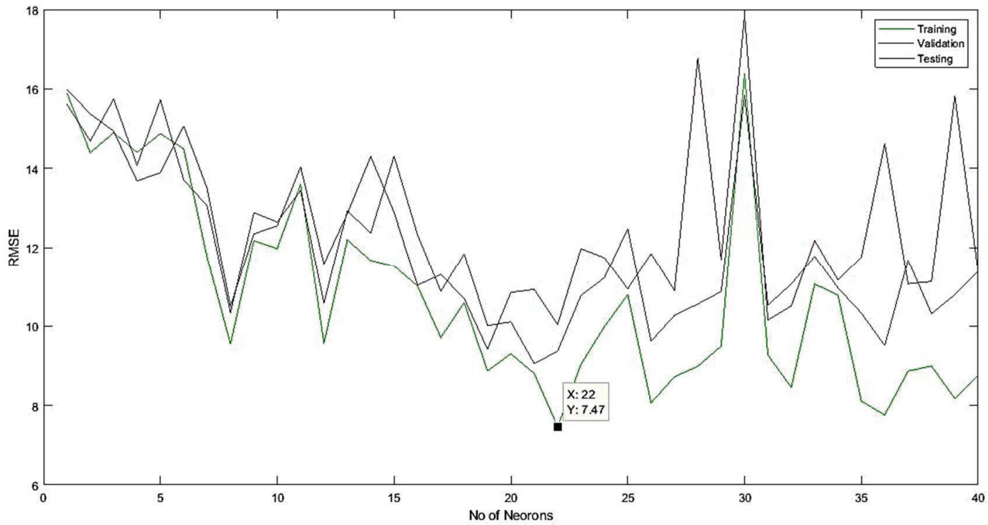

Figure 3: Optimisation of the no of neurons adopted in the ANN for prediction of compressive strength

Based upon the optimisation process shown in Figure 3, the number of neurons adopted in the ANN is modified to 19, in order to minimise the RMSE. Subsequently, the observed Predicted strength values were as follows.

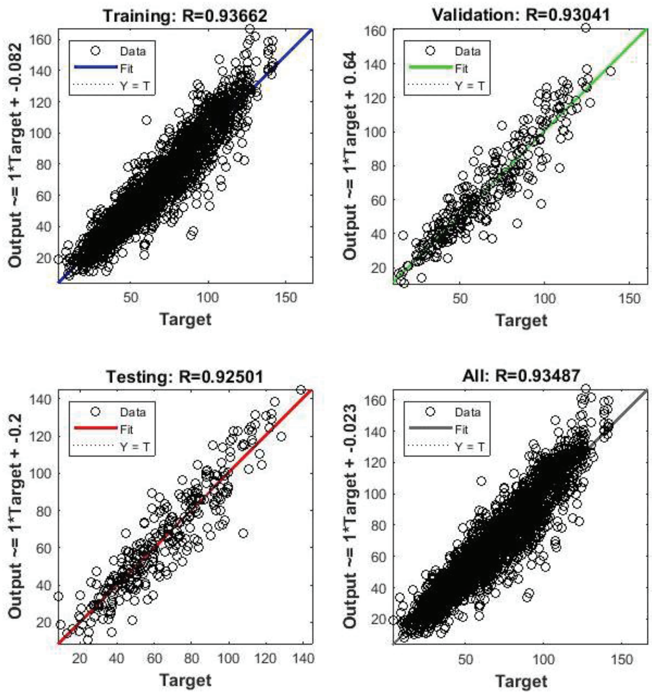

Figure 4: Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples using optimized number of neurons.

The results are summarised in Table 1. These results show reduced root-mean-square error (RMSE) upon using the optimised number of neurons.

Table 1: Performance Comparison of RMSE for prediction Compressive Strength

State	RMSE (10)	RMSE Optimised
Training	12.367	8.969
Validation	11.213	11.177
Testing	13.730	9.816

Modulus of Elasticity

Initially the model was trained with 10 number of neurons in the hidden layer, the performance of the model can be observed in the following regression plot.

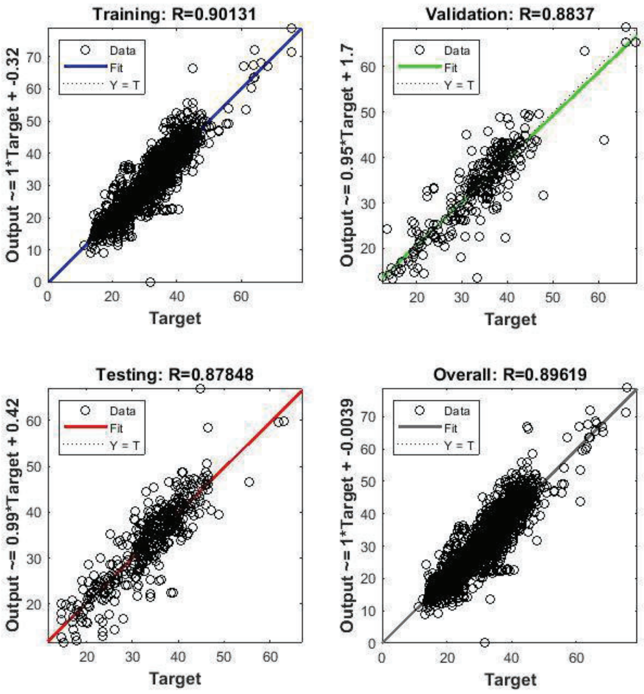

Figure 5: Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples using number of neurons (10).

The performance shown in Figure 5 has been improved using the following optimisation process.

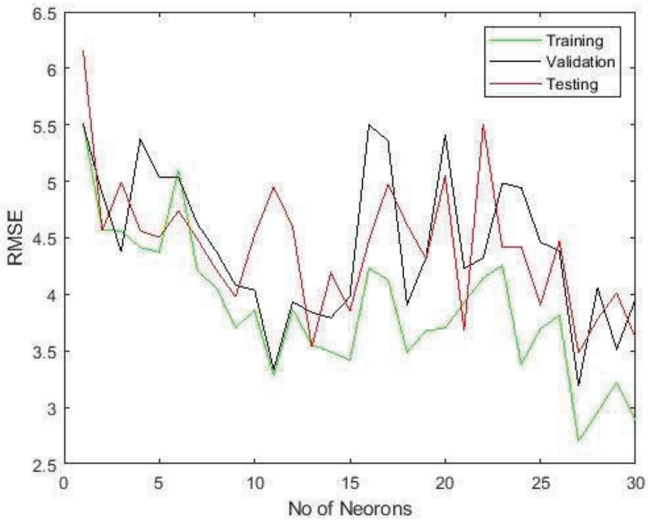

Figure 6: Optimisation of the number of neurons adopted in the ANN for prediction of modulus of elasticity

Based upon the optimisation process shown in Figure 6, the number of neurons adopted in the ANN is modified to 24, in order to minimise the RMSE. Subsequently, the linear regression for the observed predicted modulus of elasticity values were as follows.

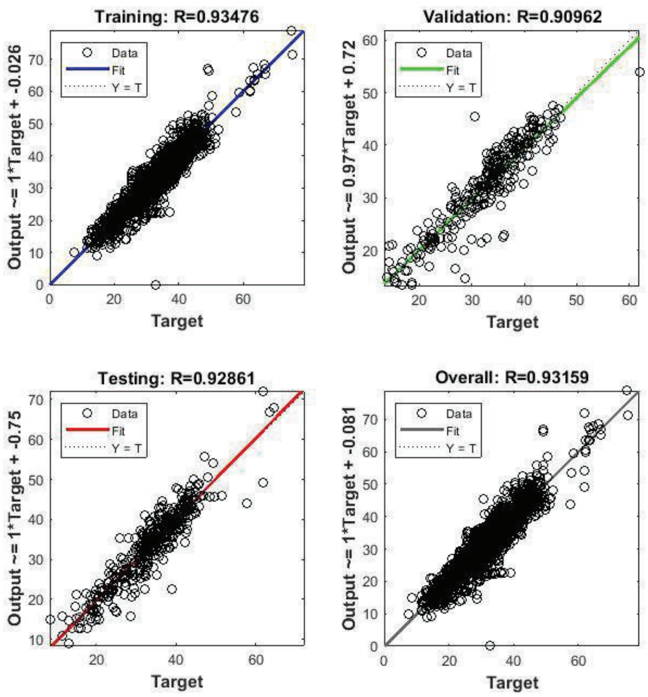

Figure 7: Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples using optimized number of neurons (24).

Significant improvement in the performance can be observed after adjusting the numbers of neurons in the hidden layer from 10 to 24. The results are summarised in table 2.

Table 2: Performance Comparison of RMSE for prediction Modulus of Elasticity

State	RMSE (10)	RMSE Optimised (24)
Training	4.465	3.037
Validation	4.492	3.44
Testing	4.871	3.41

Tensile Strength

Initially the model was trained with 10 number of neurons in the hidden layer, the performance of the model can be observed in the following regression plot.

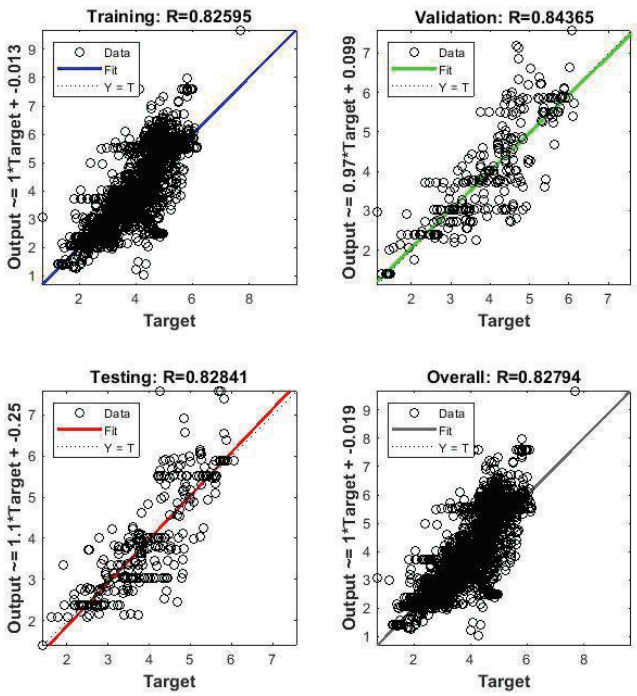

Figure 8: Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples using number of neurons (10).

Performance of the model in case of tensile strength is not good enough, exhibiting a sample correlation coefficient (r) close to 0.8. Therefore, as for the training of the ANN for compressive strength and modulus of elasticity training, the optimisation technique was adopted to calculate the optimum number of neurons. Results of the optimization process is shown as follows.

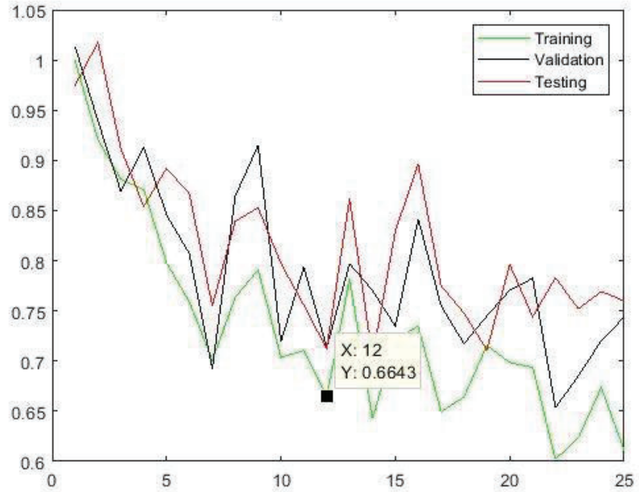

Figure 9: Optimisation of the number of neurons adopted in the ANN for prediction of tensile strength

Based upon the optimisation process shown in Figure 6, the number of neurons adopted in the ANN is modified to 15, in order the to minimise the RMSE. Subsequently, the linear regression for the observed predicted modulus of elasticity values were as follows.

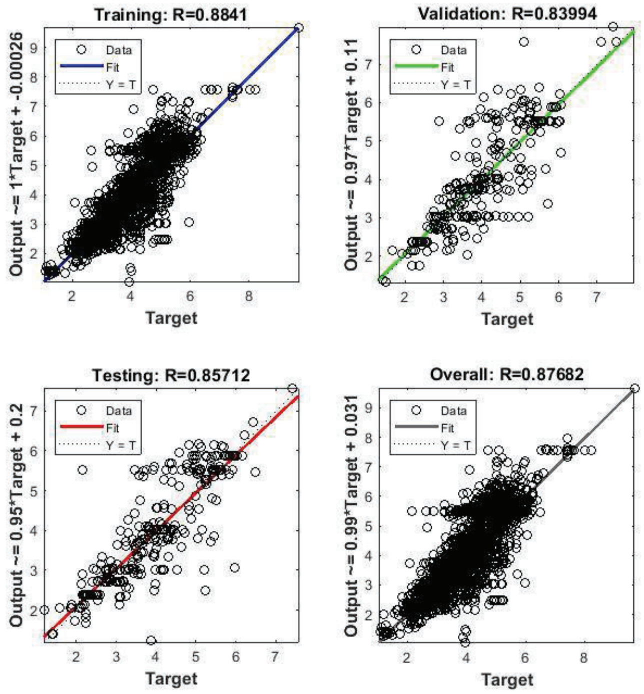

Figure 10: Predicted strength values of neural network compared with values actually observed in the laboratory for the testing examples using optimised number of neurons (24).

The results are summarised in table 3. The sample correlation coefficient (r) is observed to remain below 0.9, even after optimisation. While this result is lower than the previous predications of compressive strength and modulus of elasticity, it is still considered to signify a very strong correlation (Sheskin 2004).

Table 3: Performance Comparison of RMSE for prediction Tensile Strength

State	RMSE (10 neurons)	RMSE Optimised (15 neurons)
Training	0.750	0.62
Validation	0.735	0.732
Testing	0.732	0.717

6. RESULTS

Upon validation of the ANN model, the model is utilised to evaluate the influence of different parameters, namely the percentage content of fly ash, Ground granulated blast-furnace slag, and silica fume on the compressive strength, modulus of elasticity and tensile strength of high performance concrete (HPC).

Figure 11 presents the results of the predicted values for compressive strength by the ANN model, for admixture contents increasing in increments of 5% by mass.

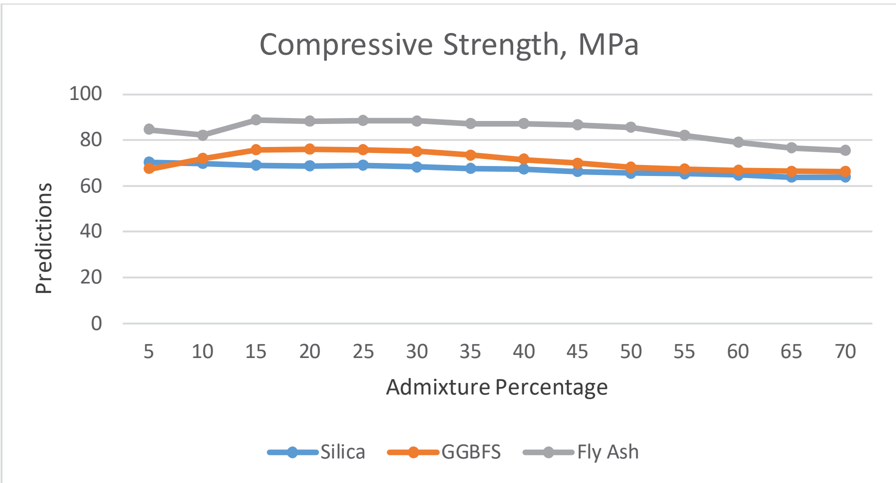

Figure 11 Predicted compressive strength of concrete at 28 days

The results show that the compressive strength increases initially with increasing content of mineral admixtures, namely microsilica, ground-granulated blast-furnace slag (GGBGS) and fly ash. However compressive strength is predicted to peak at percentage replacements ranging from 15-30% and begins to decrease beyond that. These results agree well with previous experimental studies (Bendapudi & Saha 2011; Duval & Kadri 1998; Sharma & Puvvadi 2012).

Figure 12 presents the results of the predicted values for modulus of elasticity by the ANN model, for admixture contents increasing in increments of 5% by mass.

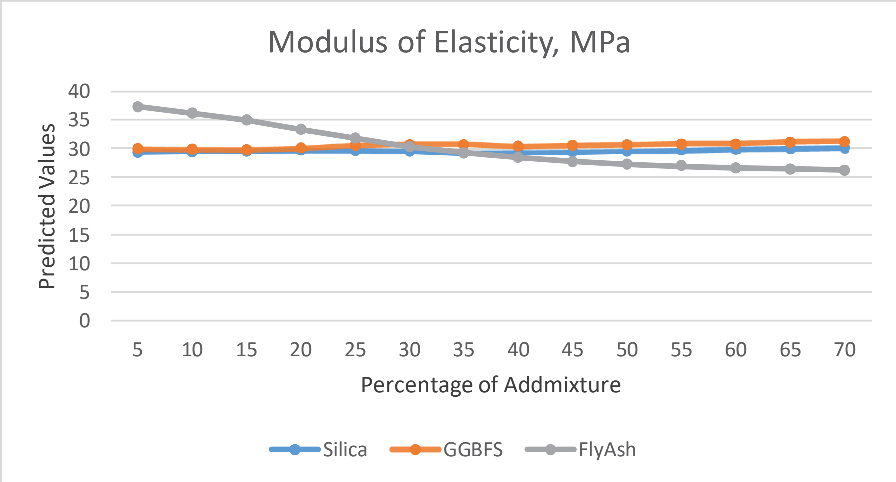

Figure 12 Predicted Modulus of elasticity of concrete at 28 days

The results show a decrease in predicted modulus of elasticity of concrete with increasing fly ash content, which is agreeable with previous research (Atchley 1959; Mohammed Ali, Zidan & Al-Eliwi 2020). For the remaining additives (Microsilica and GGBFS), the results show minimal effect of increasing the percentage of additive by weight. The influence of these additives requires further research.

Figure 13 presents the results of the predicted values for tensile strength by the ANN model, for admixture contents increasing in increments of 5% by mass.

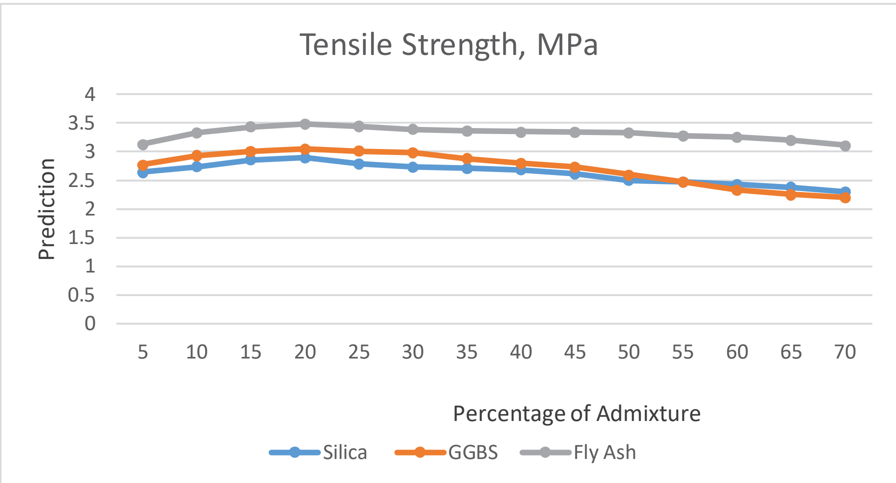

Figure 13 Predicted tensile strength of concrete at 28 days

The results show that the tensile strength increases initially with increasing content of mineral admixtures, namely microsilica, ground-granulated blast-furnace slag (GGBGS) and fly ash. However, this trend only extends until about 15% replacement by mass, beyond which the tensile strength generally decreases as admixture content increases. These results are in good agreement with results of experimental procedures reported in the literature (Mohammed Ali, Zidan & Al-Eliwi 2020; Smarzewski 2019).

7. CONCLUSION

Overall, the above results show that the ANN model is capable of predicting the mechanical properties of mineral additive enhanced high performance concretes. The results are generally in good agreement with previous experimental research. However, further research is required to enhance the accuracy of the model, and to predict mechanical properties with various percentages of multiple additives simultaneously. The results of this research may then be utilised to achieve higher utilisation of additives which would otherwise constitute hazardous waste materials in producing superior concretes for use in the construction industry, entailing both environmental and economic benefits.

REFERENCES

Atchley, B.L. 1959, 'The effects of fly-ash on dynamic modulus of elasticity of a concrete mortar', Missouri University of Science and Technology Rolla, Missouri, USA.

Bafitlhile, T. et al. 2018, 'Comparison of Levenberg Marquardt and Conjugate Gradient Descent Optimization Methods for Simulation of Streamflow Using Artificial Neural Network'.

Bendapudi, S. & Saha, P. 2011, 'Contribution of Fly ash to the properties of Mortar and Concrete', *International Journal of Earth Sciences and Engineering*, vol. 04, pp. 974-5904.

Berry, M.J.A. & Linoff, G.S. 2011, *Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management*, 3rd edn, Wiley.

Boğa, A.R. et al. 2013, 'Using ANN and ANFIS to predict the mechanical and chloride permeability properties of concrete containing GGBFS and CNI', *Composites Part B: Engineering*, vol. 45, no. 1, pp. 688-96.

Boger, Z. & Guterman, H. 1997, 'Knowledge extraction from artificial neural network models', *1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, vol. 4, pp. 3030-5 vol.4.

Chou, J.-S. et al. 2014, 'Machine learning in concrete strength simulations: Multi-nation data analytics', *Construction and Building Materials*, vol. 73, pp. 771-80.

Deb, P. et al. 2015, 'Drying Shrinkage of slag blended fly ash geopolymer concrete cured at room temperature'.

Duval, R. & Kadri, E.H. 1998, 'Influence of Silica Fume on the Workability and the Compressive Strength of High-Performance Concretes', *Cement and Concrete Research*, vol. 28, no. 4, pp. 533-47.

Ghaboussi, J. et al. 1991, 'Knowledge‐Based Modeling of Material Behavior with Neural Networks', *Journal of Engineering Mechanics*, vol. 117, no. 1, pp. 132-53.

Hyndman, R.J. & Koehler, A.B. 2006, 'Another look at measures of forecast accuracy', *International Journal of Forecasting*, vol. 22, no. 4, pp. 679-88.

McClelland, J.L. et al. 1987, *Parallel Distributed Processing, Volume 2: Explorations in the Microstructure of Cognition: Psychological and Biological Models*, vol. 2, MIT press.

Mohammed Ali, A. et al. 2020, 'Evaluation of mechanical properties of high-strength concrete with sustainable materials', *IOP Conference Series Materials Science and Engineering*, vol. 745.

Sharma, A. & Puvvadi, S. 2012, *Improvement of Strength of Expansive Soil with Waste Granulated Blast Furnace Slag*.

Sheskin, D.J. 2004, *Handbook of Parametric and Nonparametric Statistical Procedures*, 3rd ed. edn, Taylor and Francis, Hoboken.

Smarzewski, P. 2019, 'Influence of silica fume on mechanical and fracture properties of high performance concrete', *Procedia Structural Integrity*, vol. 17, pp. 5-12.

Tomosawa, F. & Noguchi, T. 1995, 'RELATIONSHIP BETWEEN COMPRESSIVE STRENGTH AND MODULUS OF ELASTICITY OF HIGH-STRENGTH CONCRETE', *Journal of Structural and Construction Engineering (Transactions of AIJ)*, vol. 60.

Yeh, I.C. 1998, 'Modeling of strength of high-performance concrete using artificial neural networks', *Cement and Concrete Research*, vol. 28, no. 12, pp. 1797-808.

Ziolkowski, P. & Niedostatkiewicz, M. 2019, 'Machine Learning Techniques in Concrete Mix Design', *Materials*, vol. 12, no. 8, p. 1256.

Zupan, J. 1994, 'Introduction to artificial neural network (ANN) methods: what they are and how to use them', *Acta Chimica Slovenica*, vol. 41, pp. 327-.