Journal of Sustainable Civil Engineering and Technology
e-ISSN: 2948-4294 | Volume 2 Issue 1 (March 2023), 36-44
https://joscetech.uitm.edu.my
https://doi.org/10.24191/jscet.v2i1.36-44

An MRFO Based Artificial Neural Network Based Prediction of Geopolymer Containing Waste Fibre Performance

Reshma Raj Parameswaran Vijayalekshmi[1], Simon Judes Sujatha[2]

[1]Research Scholar, Department of Civil Engineering, Government Engineering College, Nagercoil, India.

[2]Department of Civil Engineering, Government Engineering College, Nagercoil, India.

*Corresponding author: reshmaraj6662@gmail.com.

Received: 13 January 2023 / Accepted: 05 March 2023 / Published online: 28 March 2023

Abstract

Geopolymer concrete (GPC) based on fly ash (FA) is being studied as a possible alternative solution with a lower environmental impact rather than the use of Portland cement based composites. However, the accuracy of the strength prediction still needs to be improved. This study was based on the investigation of various types of machine learning (ML) approaches to predict the compressive strength (C-S) of GPC. This paper proposes a novel approach to predict the compressive strength (C-S) of GPC utilizing Manta Ray Foraging Optimization (MRFO) based on Artificial Neural Network (ANN). Manta ray has three foraging behaviors like chain foraging, cyclone foraging, and somersault foraging for solving various optimization problems. The coefficient of determination (R^2) is used to measure how accurate the results are, which usually ranged from 0 to 1. ANN is utilized to forecast the optimized outcomes. Various statistical assessment criteria, such as the coefficient of determination, the mean-absolute percentage deviation, and root-mean-square deviation, were used to evaluate the efficiency of the developed models. The cross-validation technique (k-fold) confirmed the model's performance. The results indicated that the ANN-MRFO model predicted the C–S of FA-GPC mixtures better than the other models. Also, the sensitivity analysis of the proposed model shows that the curing temperature, the ratio of alkaline liquid to the binder, and the amount of sodium silicate are the most important parameters for estimating the C–S of the FA-GPC.

Keywords: *Geopolymer concrete, compressive strength, Artificial Neural Network, Manta Ray Foraging Optimization, Global optimization.*

1. Introduction

Concrete is one of the most popular materials used in modern construction, and cement is known as the main binder of the concrete structure. The applications of geopolymer concrete for structural repair and rehabilitation works show higher durability properties; however, the knowledge of the long-term performance of the geopolymer composites remains limited, especially in corrosive environments such as marine infrastructural applications. Soft computing tools and techniques are now being widely adopted by researchers in the field of civil engineering owing to the accuracy in predictions, especially with trained network models such as artificial neural networks (ANN) (Tang et.al., 2022; Mashrei, et.al., 2013; Rahman et al., 2021). Artificial neural networks are a soft computing tool that can provide self-learned, logical prediction patterns based on the framework of an input layer for datasets, a hidden layer for nodes assigning weights, and an output layer for targeted results (Rahman e.tal., 2021; Asteris et.al., 2016; Alnedawi et.al., 2019). The production process of geopolymer concrete also meets the circularity principles in which the reliability of virgin raw materials is drastically reduced (Chong, B.W.; et al., 2021).ANNs are preferred owing to their higher error tolerance, precision in decision-making, and ability to solve complex non-linear relations (Łach et.al., 2021). However, using cement leads to a negative effect on the environment due to the emission of carbon dioxide generated during the production of cement, according to Davidovits. As a consequence, the influences of climate change, the greenhouse effect, and calamities have serious threats to human life and the environment. The demand for research regarding friendly environmental construction materials, a decrement the carbon dioxide emissions into the air, and a reduction of cost are important needs for sustainable development all around the world. Therefore, many works have been carried out to develop a new eco-friendly and green material used to alter cement in concrete.

Journal of Sustainable Civil Engineering and Technology
e-ISSN: 2948-4294 | Volume 2 Issue 1 (March 2023), 36-44
https://joscetech.uitm.edu.my
https://doi.org/10.24191/jscet.v2i1.36-44

"Geopolymers" was a term invented by Davidovits in the 1970s which can be used to describe new materials or alternative binders in concrete. Geopolymers were investigated by combining source materials such as slag, fly ash, and minerals to replace cement and alkaline solution. There are many advantages when using geopolymer composites, such as higher mechanical performance, low production cost, good properties like a low creep and drying shrinkage, excellent fire resistance, and a low corrosion rate.Geopolymer concretes produced by the alkali activation of alumino-silicate-rich supplementary cementitious materials, including fly ash and slag, have been proven to offer higher strength and better resistance to aggressive environments (Rahman, S.K. et al., 2021; Rahman, S.K. et al., 2022). The geopolymer concrete exhibits similar brittleness and shrinkage properties to conventional cement concrete (Omer, L.M.et.al., 2022; Goswami, A.P.2021). The experimental results indicated that the flexural strain capacity of BF is sensitive to stress accumulation due to the cement hydration products in the matrix-fibre interface.(Girgin, Z.C.; Yıldırım, M.T.;2016). This study reviews current developments in the manufacturing of mine tailings-based geopolymer composites from industrial waste as a possible sustainable building material (Krishna, R.S.; et al.,2021). The development of new, sustainable, low-CO2 construction materials is essential if the global construction industry is to reduce the environmental footprint of its activities, which is incurred particularly through the production of Portland cement (Provis, J.L.; et al.,2014). Cement is the main component of concrete, a widely used building material. Cement production requires substantial energy, exhausts natural resources, and causes CO_2 emissions. Efforts are being undertaken to develop a concrete binder instead of cement.Cement is the main component of concrete, a widely used building material. Cement production requires substantial energy, exhausts natural resources, and causes CO2 emissions. Efforts are being undertaken to develop a concrete binder instead of cement (Yang, H et al.,2022). More importantly, geopolymers have obvious advantages in immobilizing heavy metals in solid wastes. Therefore, it can demonstrate geopolymer is a sustainable and environmentally friendly "green material"(Ren, B.;et al.,2020). Compressive strength can be improved with the replacement of fly ash with other waste materials; however, it is strongly dependent on the mix design, which highlights the importance of Si/Al ratio, NaOH concentration, and SS/SH ratio as a factor (Podolsky, Z.; et al.,2021). The widespread industry adoption of geopolymer concrete has the potential to positively contribute to environmental sustainability in both the industrial and construction sectors, through the recycling of waste materials, and the reduction in carbon emissions. (Mohajerani, A.;et al.,2019) A familiar metaheuristic significantly performs the test result in the proposed method. In MRFO algorithm the study of structure is explained. It is derived from natures which possess basic theories or mathematical models in this method (Farooq, F.;et al.,2021). A comparison with existing research results shows that MSFRC has achieved an ideal effect of high temperature resistance. The multi-scale hybrid fiber system significantly alleviates the deterioration of cement-based composite's mechanical properties under high temperatures. (Li, L.;et al.,2021)This study aims to examine the strength of fly ash geopolymer concrete and reduce carbon emissions. In this investigation, the flexural test is done for conventional and geopolymer concrete (GPC) beam samples after the fulfillment of the rest period and 24 h steam curing at 60 °C. The experimental results prove that the initial characteristics of both specimens are almost similar. When GPC specimens reached the service, yield, and failure stages, the load carrying capacity, and defection increased up to 21.5 and 8.75% (Alex, A.G.,et al.,2022).When the beam specimens are allowed to reach the service yield and failure stage (in both the CB and GB), the defection in GB is higher than the CB, i.e., it increases up to 21.5% and 8.75%, respectively, on the above two stages. Better crack propagation was observed in GB than in CB. Hence, this study upholds GB is a better alternative material for CB, within the limit of applied specifications (Alex, A.G., et al.,2022).The incorporation of SiC particles increases the mechanical strength and wear performance of Al composites. However, the ejection of these particles can reduce the wear performance of Al composites under severe conditions. The addition of Gr particles helps in the formation of a thick and extensive tribolayer on the wear surface. This layer reduces direct contact between the rubbing surfaces, thereby decreasing the wear (Singh, J. 2016).A correlation study was undertaken to compare the fly ash precursor chemical and crystallographic compositions as well as particle size distribution, with the mechanical and chemical characteristics of the resulting geopolymer the strength increased compared to CC (Diaz, E.I.;et al.,2010).Geopolymer concrete produced using 100% fly ash is a similar sustainable construction material capable of replacing Portland Cement (PC) concrete. As a replacement for PC, fly ash seems to be a sustainable solution, however, the benefits from the production process of fly ash geopolymer (FAGP) concrete is the subject of considerable debate. In addition, factors such as local availability and transportation issues could potentially increase the emission profile of FAGP concrete.(Sandanayake, M.;et al.,2018)Various studies have reported using different types of composites such as glass, carbon, basalt, polyethylene, polypropylene, steel, etc., as fibre reinforcements for geopolymer concrete (Shaikh, F.; Haque, S.;2018, High, C.;et al.,2015). Researchers focus on geopolymer binders as an alternative so that less energy consumption, reduce carbon emission, with less waste materials can be obtained.

Metaheuristic approaches one of the dominant and well-known tools that efficiently solve optimization problems. A novel approach Manta Ray Foraging Optimization (MRFO) is developed and it has three foraging behaviors including chain foraging, cyclone foraging, and somersault foraging. The method mimics the human brain, where the hidden neurons which are the dependent variables in the network are correlated with the input parameters to produce the desired output (Golafshani, E.M.; et al., 2015;). It is easy and simple to implement. To enhance the selected responses, ANN is utilized to find out the unique set of

Journal of Sustainable Civil Engineering and Technology
e-ISSN: 2948-4294 | Volume 2 Issue 1 (March 2023), 36-44
https://joscetech.uitm.edu.my
https://doi.org/10.24191/jscet.v2i1.36-44

input variables. A limited exploration indicates in the literature. Thus, this research presents a detailed overview of the permeability characteristics of self-compacting geopolymer concrete mixes made from recycled industrial waste products

This study uses both the individual ANN and Manta Ray Foraging Optimization (MRFO) ML algorithm to forecast the compressive strength of high calcium fly ash-based geopolymer concrete. The ANN and boosting approaches were incorporated for the prediction aspect. The evaluation of the errors, mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) was part of this study, which confirms the model's accuracy. The statistical checks and k-fold cross-validation process were also adopted to confirm the model's accuracy. In addition, the sensitivity analysis was also carried out to evaluate the contribution of all input parameters towards the prediction of compressive strength of high calcium fly ash-based GPC. Figure 1 shows a schematic illustration of the GP concrete manufacturing process.

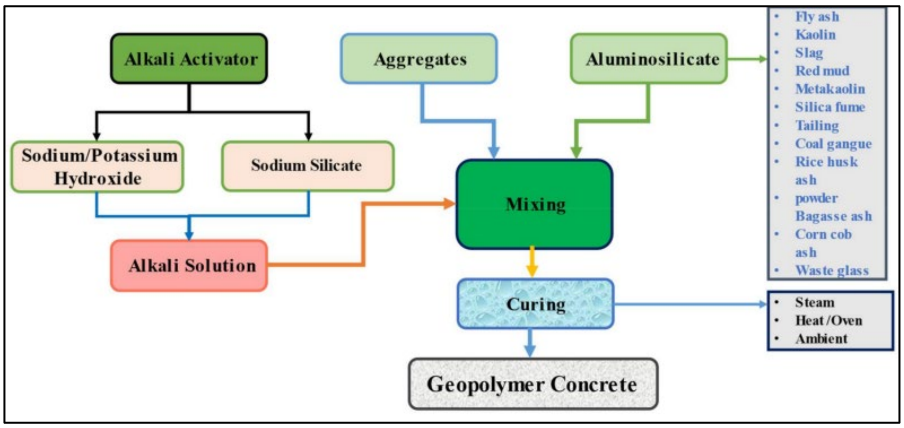

Figure 1. Schematic illustration of the GP concrete manufacturing process

2. Methodology

Artificial Neural Network

The ANN consists of an input unit, a hidden unit, and an output unit. The initial unit is known as the input unit used for mapping the variables in the network. The final unit is the output unit and the units between both input and output units are known as hidden units. The node within the same layer does not interconnect and they are connected by processing nodes of these units. The units are denoted by nodes, and in each node of the network, the output is computed in two phases. ANN has many benefits such as arbitrary decision boundary capabilities, various kinds of data, and non-parametric nature. Considering, all patterns in the neural network take place for learning and training the data in an iterative way. ANN is called data dependent models. Therefore, ANN can successfully utilize for planning input to a desired output and for learning the patterns in the dataset delivered. In multilayer perceptron the neural network model commonly utilized is a feed forward neural network.Fig.2 shows the structure of ANN model.

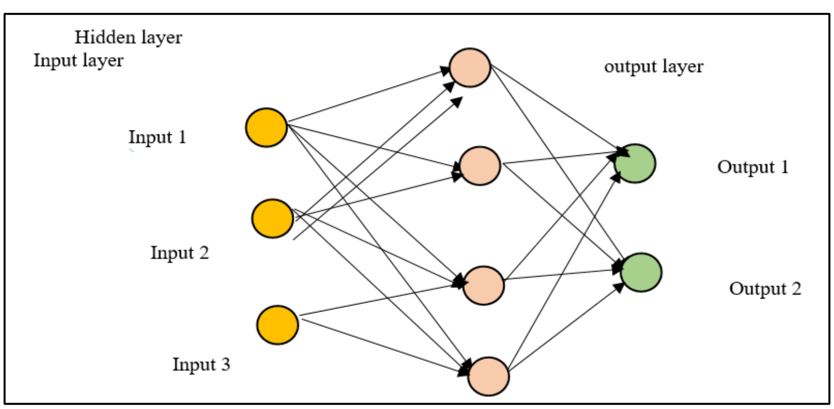

Figure 2. Structure of Artificial Neural Network

Journal of Sustainable Civil Engineering and Technology
e-ISSN: 2948-4294 | Volume 2 Issue 1 (March 2023), 36-44
https://joscetech.uitm.edu.my
https://doi.org/10.24191/jscet.v2i1.36-44

The proposed ANN approach utilizes Eqn- (1) to calculatethe percentage error,

$$\text{\% of predicted error} = \frac{Experimental - ANN\ data}{Experimental\ data} \times 100 \quad (1)$$

2.1 Manta Ray Foraging Optimization

One of the largest known marine living being is Manta rays [9]. They are subdivided into two: reef manta rays and giant manta rays. They can live an average of about 20 years. A huge amount of plankton is required by manta rays for their food. Manta rays implement three aging intelligent tactics such as chain foraging, cyclone foraging, and somersault foraging.

2.1.1. Chain foraging

When a manta ray locates itself, it searches for plankton and swims in its direction. It forms a foraging chain by lining up head to tail. Each manta ray moves not only toward the food but also toward the manta ray in front of them. Each manta ray got the best solution so far and the solution in front of them. Eqn (2) denotes the chain foraging.

$$y_i^d(t+1) = \begin{cases} y_i^d(t) + r \cdot \left(y_{best}^d(t) - y_i^d(t)\right) + \alpha \cdot \left(y_{best}^d(t) - y_i^d(t)\right) i = 1 \\ y_i^d(t) + r \cdot \left(y_{i-1}^d(t) - y_i^d(t)\right) + \alpha \cdot \left(y_{best}^d(t) - y_i^d(t)\right) i = 2, \ldots, m \end{cases} \text{----} \quad (2)$$

$$\alpha = 2 \cdot r \cdot \sqrt{|\log(r)|} \text{-----} \quad (3)$$

$y_i^d(t)$ *denotes the* i[th]manta ray; the arbitrary vector r ranges between 0 and, αdenotes the coefficient weight,$y_{best}^d(t)$ represents the best area in search of food plankton$y_{(i-1)}^d(t)$represent themodifiedi[th]manta ray location, where d denotes the dimension

2.1.2. Cyclone foraging

Aside from spiraling nearer to the food, the individual swims in front of it. Manta rays' spiral-shaped movement can be represented in Eqn(4)

$$\begin{cases} X_i(t+1) = X_{best} + r \cdot \left(X_{i-1}(t) - X(t)\right) + e^{bw} \cdot \cos(2\pi w) \cdot \left(X_{best} - X_i(t)\right) \\ Y_i(t+1) = Y_{best} + r \cdot \left(Y_{i-1}(t) - Y_i(t)\right) + e^{bw} \cdot \sin(2\pi w) \cdot \left(Y_{best} - Y_i(t)\right) \end{cases} ------(4)$$

Here, w denotes an arbitrary value between 0 to 1.

The Cyclone foraging is computed as,

$$y_i^d(t+1) = \begin{cases} y_{best}^d + r \cdot \left(y_{best}^d(t) - y_i^d(t)\right) + \beta \cdot \left(y_{best}^d(t) - y_i^d(t)\right) \quad i = 1 \\ y_{best}^d + r \cdot \left(y_{i=1}^d(t) - y_i^d(t)\right) + \beta \cdot \left(y_{best}^d(t) - y_i^d(t)\right) \quad i = 2, \ldots, m \end{cases} \text{----------} \quad (5)$$

$$\beta = 2e^{r1\frac{T-t+1}{T}} \cdot \sin(2\pi r_1) \quad (6)$$

Here, the total number of iterations is denoted as T, β represents the weight coefficient and r_1 denotes arbitrary numbers varying in [0.1]. Cyclone foraging also improves exploration, which is an arbitrary search procedure performed according to the food. To obtain the global best solution, each individual may be pushed to hunt for a new location, regardless of the present best one. The mathematical equation is described below,

$$y_{rand}^d = Lb^d + r \cdot (Ub^d - Lb^d) \quad (7)$$

$$y_i^d(t+1) = \begin{Bmatrix} y_{rand}^d + r \cdot \left(y_{rand}^d - y_i^d(t)\right) + \beta \cdot y_{rand}^d - y_i^d(t)) \; i = 1 \\ y_{rand}^d + r \cdot \left(y_{i=1}^d(t) - y_i^d(t)\right) + \beta \cdot \left(y_{rand}^d - y_i^d(t)\right) i = 2, \dots N \end{Bmatrix} \quad - \qquad (8)$$

Where x_{rand}^ddenotes an arbitrary location in the search area, L$b^d$and Ub^drepresents the maximum and minimum bounds of the dth dimension

2.1.3. Somersault foraging:

Each member spins around the food and somersaults into a different location. They constantly adjust their location in areas with more plankton. The following is a description of the mathematical model:

$$y_i^d(t+1) = y_i^d(t) + S \cdot \left(r_2 \cdot y_{best}^d - r_3 \cdot y_i^d(t)\right), i = 1, \dots, m \qquad (9)$$

Here, the somersault factor is denoted as S which agrees with the somersault series of manta rays and S=2, $r_2$and r_3 represents arbitrary numbers between 0 and 1. The number of iterations in the outcome is inversely related to the range of somersaults.

2.1.4 Proposed Approach

Manta ray foraging optimization algorithm is a recently introduced algorithm with various models of foraging behaviours that are considered for training the artificial neural network(ANN) in the proposed method. The convergence and divergence of ANN are influenced by optimizing the connection weight of feed forward (FF) neural network models. In the proposed approach, MRFO is utilised in the search space for finding the optimal value of network weight and bias. This process of initialising the network weight and bias using optimal values and the results indicate that the artificial neural network optimized in MRFO exhibits greater flexibility and accuracy in comparison with conventional models. In this, MRFO is taken to train the data in ANN with a single hidden unit. While modeling the proposed approach, the estimation of the fitness value function and the initialization of parameters is considered. In this process, to initialize the parameters and to update the position of manta ray can be predetermined as one-dimensional vector for reproducing the optimistic neural network. The proposed model consists of three layers such as network weights linking the unit and hidden unit, network weights linking the hidden unit and output unit, and bias. The workflow of the proposed mode is shown in figure 3.

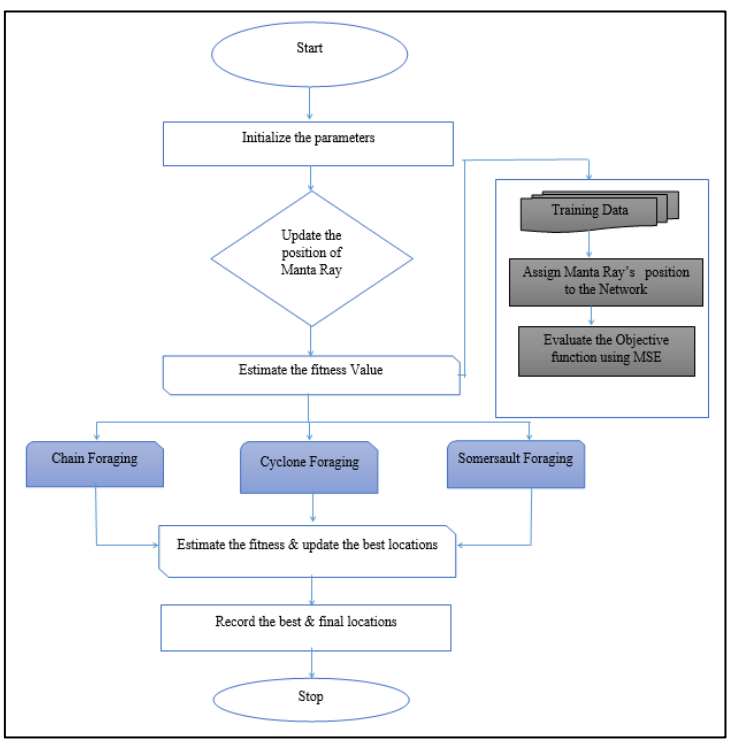

Figure 3. Flowchart of the proposed MRFO - ANN model.

Journal of Sustainable Civil Engineering and Technology
e-ISSN: 2948-4294 | Volume 2 Issue 1 (March 2023), 36-44
https://joscetech.uitm.edu.my
https://doi.org/10.24191/jscet.v2i1.36-44

Each solution is taken from a vector of a real number with an interval in the range of -1 to 1. Mean Square Error (MSR) has been utilized for minimizing and optimizing the network weight and bias for measuring the fitness value in manta ray foraging optimization algorithm. It may be defined that the quantity of difference between the actual values and predicted values produced by the neural network of all the training data. MRFO is utilized for training the neural network after the estimation of fitness function and the representation of solutions.

3. Experimental Tests

The statistical findings from the MRFO - ANN between the targeted result obtained from the experimental work and the forecasted outcome can be seen in Figure 4. The result of the ANN model reveals that the accuracy level was impressive towards the prediction of CS of flays ash-based GPC as indicated by the coefficient correlation (R^2) value (0.87). However, the distribution of the errors from the actual and forecasted results is depicted in Figure 5. The errors' maximum, minimum, and average values were 9.56 MPa, 0.85, and 3.86 MPa, respectively. Moreover, it was noted that 25.8% of the error data lie between 0 to 2 MPa, and 48.38% of this data was reported between 2 MPa to 5 MPa. However, only 19.35% of the error data was observed to be above 5 MPa..

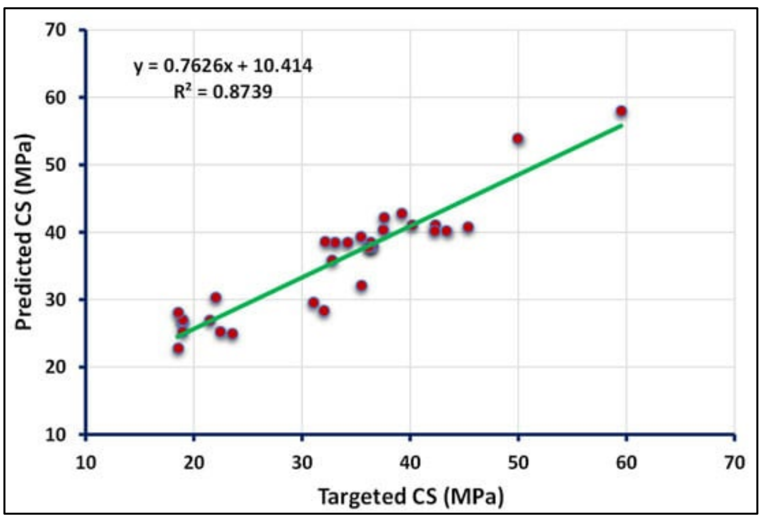

Figure 4. Relationship between the targeted and predicted results obtained from the MRFO - ANN model

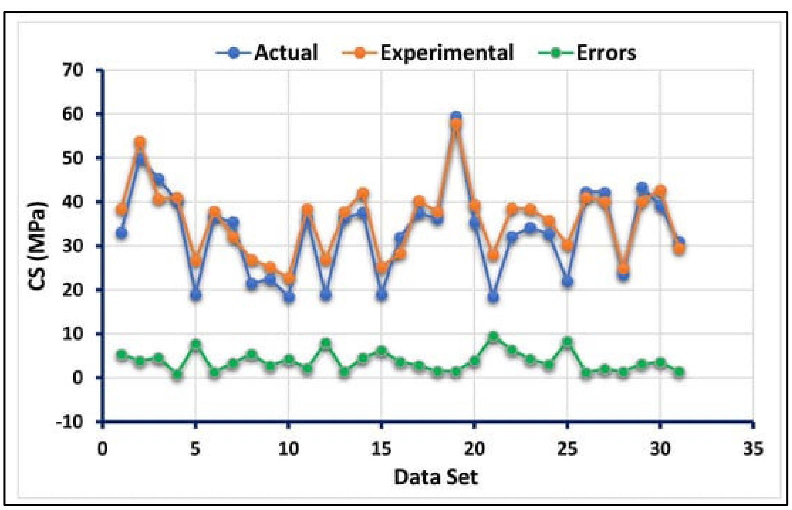

Figure 5. Error distribution of the targeted and predicted results from the MRFO - ANN model

The data of the parameters (R^2, MAE, MSE, and RMSE) obtained from the data of the employed algorithmMRFO - ANN model is taken for the k-fold cross-validation process as depicted in Figure 6 and Figure 7. However, the maximum, minimum, and average values of MSE during the process of k-fold cross-validation for MRFO - ANN model are 1658.28 MPa, 14.33 MPa, and 612.97 MPa, respectively, as shown in Figure 6. In addition, the maximum values of MAE, RMSE, and R^2 were noted as 42.76 MPa, 40.72 MPa, and 0.98, respectively. In comparison, the maximum, minimum, and average results of MSE for boosting approach were 601.90 MPa, 10.41 MPa, and 132.96 MPa, respectively, and can be seen in Figure 7. However, the maximum values reported for MAE, RMSE, and R^2 are 47.51 MPa, 24.53 MPa, and 0.95, respectively.

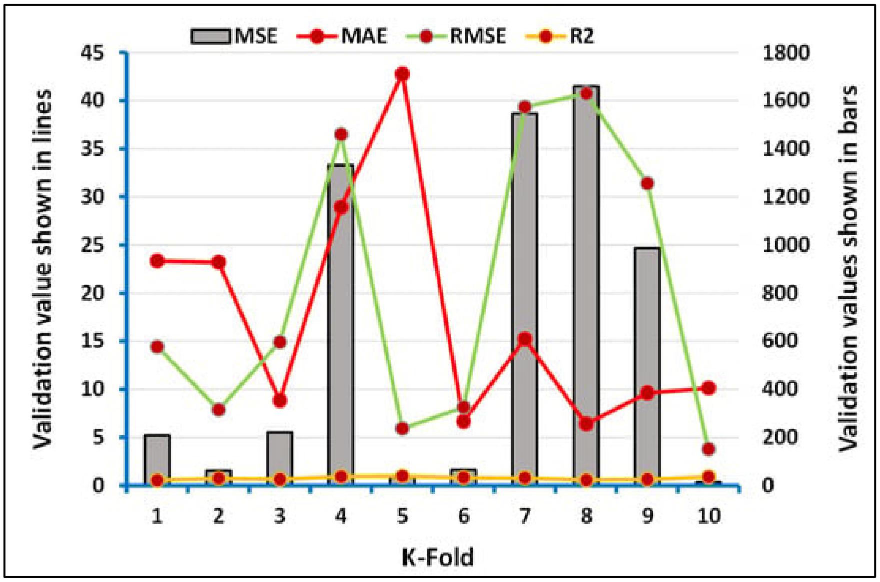

Figure 6. Representation of the statistics for k-fold cross-validation of theMRFO - ANN model

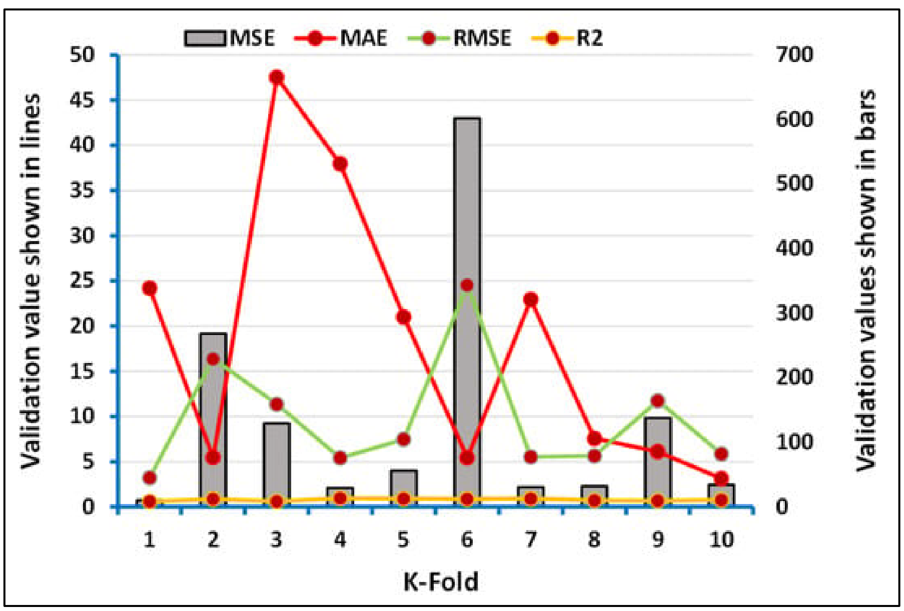

Figure 7. Representation of the statistics for k-fold cross-validation of the boosting model

To check the influence of each variable on the prediction of CS of high calcium fly-ash-based GPC, the analysis was carried out known as the sensitivity analysis. Since the input parameters play a key role in the accuracy of employed models for the prediction aspect, it is also necessary to know the effect of input parameters individually on the predicted outcome. The contribution of each input parameter towards the forecasted output of the CS of GPC can be seen in Figure 8.

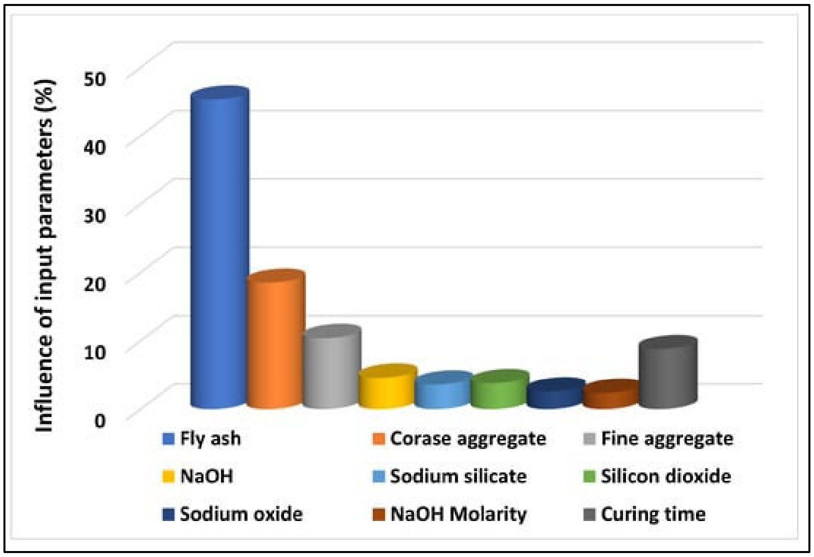

Figure 8. Influence of input parameters towards the prediction of outcome (CS) of GPC

4. Conclusion

An artificial neural network is combined with the Manta Ray Foraging Optimization Algorithm in the proposed model to predict the compressive strength (C-S) of GPC. This work proposes a new foraging behavior optimization approach called Manta Ray Foraging Optimization (MRFO).To replicate the way manta rays forage for food, this algorithm uses three foraging operators: chain foraging, cyclone foraging, and somersault foraging. The results of hardness and tensile strength are compared to the experimental outcomes and ANN is anticipated to be more accurate. The prediction findings are in acceptable agreement with the experimental data when artificial neural networks are optimized using the manta ray foraging optimization algorithm. Furthermore, the ANN-MRFO model can be utilized for to compressive strength (C-S) of GPC. For future development, the binary MRFO might be introduced to solve complex discrete problems.

Acknowledgement

Not applicable

Conflicts of Interest

The authors declare no conflict of interest.

References

Alnedawi, A., Al-Ameri, R., & Nepal, K. P. (2019). Neural network-based model for prediction of permanent deformation of unbound granular materials. *Journal of Rock Mechanics and Geotechnical Engineering*, *11*(6), 1231-1242.

Alex, A. G., Gebrehiwet, T., Kemal, Z., & Subramanian, R. B. (2022). Structural Performance of Low-Calcium Fly Ash Geo-polymer Reinforced Concrete Beam. *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, 1-12.

Alex, A. G., Gebrehiwet Tewele, T., Kemal, Z., & Subramanian, R. B. (2022). Flexural Behavior of Low Calcium Fly Ash Based Geopolymer Reinforced Concrete Beam. *International Journal of Concrete Structures and Materials*, *16*(1), 1-11.

Asteris, P.G.; Kolovos, K.G.; Douvika, M.G.; Roinos, K. Prediction of self-compacting concrete strength using artificial neural networks. Eur. J. Environ. Civ. Eng. 2016, 20, s102–s122.

Chong, B. W., Othman, R., Putra Jaya, R., Mohd Hasan, M. R., Sandu, A. V., Nabiałek, M., ... & Abdullah, M. M. A. B. (2021). Design of experiment on concrete mechanical properties prediction: a critical review. *Materials*, *14*(8), 1866.

High, C., Seliem, H. M., El-Safty, A., & Rizkalla, S. H. (2015). Use of basalt fibers for concrete structures. *Construction and Building materials*, *96*, 37-46.

Diaz, E. I., Allouche, E. N., & Eklund, S. (2010). Factors affecting the suitability of fly ash as source material for geopolymers. *Fuel*, *89*(5), 992-996.

Farooq, F., Jin, X., Javed, M. F., Akbar, A., Shah, M. I., Aslam, F., & Alyousef, R. (2021). Geopolymer concrete as sustainable material: A state of the art review. *Construction and Building Materials*, *306*, 124762.

Hillary, J. J. M., Ramamoorthi, R., Joseph, J. D. J., & Samuel, C. S. J. (2020). A study on microstructural effect and mechanical behaviour of Al6061–5% SiC–TiB2 particulates reinforced hybrid metal matrix composites. *Journal of Composite Materials*, *54*(17), 2327-2337.

Girgin, Z. C., & Yıldırım, M. T. (2016). Usability of basalt fibres in fibre reinforced cement composites. *Materials and Structures*, *49*(8), 3309-3319.

Goswami, A. P. (2021). Determining physico-chemical parameters for high strength ambient cured fly ash-based alkali-activated cements. *Ceramics International*, *47*(20), 29109-29119.

Golafshani, E. M., Rahai, A., & Sebt, M. H. (2015). Artificial neural network and genetic programming for predicting the bond strength of GFRP bars in concrete. *Materials and structures*, *48*(5), 1581-1602.

Haddad, R., & Haddad, M. (2021). Predicting fiber-reinforced polymer–concrete bond strength using artificial neural networks: A comparative analysis study. *Structural Concrete*, *22*(1), 38-49.

Krishna, R. S., Shaikh, F., Mishra, J., Lazorenko, G., & Kasprzhitskii, A. (2021). Mine tailings-based geopolymers: Properties, applications and industrial prospects. *Ceramics International*, *47*(13), 17826-17843.

Łach, M., Kluska, B., Janus, D., Kabat, D., Pławecka, K., Korniejenko, K., ... & Choińska, M. (2021). Effect of Fiber Reinforcement on the Compression and Flexural Strength of Fiber-Reinforced Geopolymers. *Applied Sciences*, *11*(21), 10443.

Li, L., Khan, M., Bai, C., & Shi, K. (2021). Uniaxial tensile behavior, flexural properties, empirical calculation and microstructure of multi-scale fiber reinforced cement-based material at elevated temperature. *Materials*, *14*(8), 1827.

Mashrei, M. A., Seracino, R., & Rahman, M. S. (2013). Application of artificial neural networks to predict the bond strength of FRP-to-concrete joints. *Construction and Building Materials*, *40*, 812-821.

Mohajerani, A., Suter, D., Jeffrey-Bailey, T., Song, T., Arulrajah, A., Horpibulsuk, S., & Law, D. (2019). Recycling waste materials in geopolymer concrete. *Clean Technologies and Environmental Policy*, *21*(3), 493-515.

Omer, L. M., Gomaa, M. S., Sufe, W. H., Elsayed, A. A., & Elghazaly, H. A. (2022). Enhancing corrosion resistance of RC pipes using geopolymer mixes when subjected to aggressive environment. *Journal of Engineering and Applied Science*, *69*(1), 1-16.

Podolsky, Z., Liu, J., Dinh, H., Doh, J. H., Guerrieri, M., & Fragomeni, S. (2021). State of the art on the application of waste materials in geopolymer concrete. *Case Studies in Construction Materials*, *15*, e00637.

Provis, J. L., & Bernal, S. A. (2014). Geopolymers and related alkali-activated materials. *Annual Review of Materials Research*, *44*, 299-327.

Rahman, S. K., & Al-Ameri, R. (2021). A newly developed self-compacting geopolymer concrete under ambient condition. *Construction and Building Materials*, *267*, 121822.

Rahman, S. K., & Al-Ameri, R. (2021). Experimental investigation and artificial neural network based prediction of bond strength in self-compacting geopolymer concrete reinforced with basalt FRP bars. *Applied Sciences*, *11*(11), 4889.

Rahman, S. K., & Al-Ameri, R. (2022). Marine Geopolymer Concrete—A Hybrid Curable Self-Compacting Sustainable Concrete for Marine Applications. *Applied Sciences*, *12*(6), 3116.

Ren, B., Zhao, Y., Bai, H., Kang, S., Zhang, T., & Song, S. (2021). Eco-friendly geopolymer prepared from solid wastes: A critical review. *Chemosphere*, *267*, 128900.

Sandanayake, M., Gunasekara, C., Law, D., Zhang, G., & Setunge, S. (2018). Greenhouse gas emissions of different fly ash based geopolymer concretes in building construction. *Journal of cleaner production*, *204*, 399-408.

Shaikh, F., & Haque, S. (2018). Behaviour of carbon and basalt fibres reinforced fly ash geopolymer at elevated temperatures. *International Journal of Concrete Structures and Materials*, *12*(1), 1-12.

Singh, F. characteristics and tribological behavior of Al. *SiC/Gr hybrid aluminum matrix composites: a review, Friction*, (4), 191.

Tang, Y. X., Lee, Y. H., Amran, M., Fediuk, R., Vatin, N., Kueh, A. B. H., & Lee, Y. Y. (2022). Artificial Neural Network-Forecasted Compression Strength of Alkaline-Activated Slag Concretes. *Sustainability*, *14*(9), 5214.

Yang, H., Liu, L., Yang, W., Liu, H., Ahmad, W., Ahmad, A., ... & Joyklad, P. (2022). A comprehensive overview of geopolymer composites: A bibliometric analysis and literature review. *Case Studies in Construction Materials*, *16*, e00830.