ANN-Based Prediction of Compressive Strength in Glass Wool Reinforced Brick

Yashwanth Pamu[1] and *Prasanna* SVSNDL[2]

[1]CVR College of Engineering, Hyderabad, Telangana, India
[2]University College of Engineering, Osmania University, Hyderabad, Telangana, India

Abstract. The construction industry continuously seeks innovative materials and methodologies to enhance structural integrity while minimizing environmental impact. This study investigates the predictive capabilities of Artificial Neural Networks (ANN) in estimating the compressive strength of clay brick. Employing a dataset derived from comprehensive experimental trials encompassing varying compositions and curing conditions, an ANN model was developed and trained to predict the compressive strength of glass wool reinforced composite bricks. The inputs to the ANN comprised key parameters including the proportions of glass wool content, load at failure, area of cross-section and burning temperature. The model was optimized through iterative training processes to attain robustness and accuracy in predicting compressive strength. Subsequently, validation was performed using separate test datasets to evaluate the model's generalization capacity. The results demonstrate the efficacy of the ANN model in accurately forecasting the compressive strength of glass wool reinforced clay brick. The analysis reveals nuanced correlations between glass wool content, load at failure, area of cross-section and burning temperature, and the resultant strength, shedding light on the intricate dynamics governing these composite materials. This ANN-based predictive approach presents a useful tool for engineers and stakeholders in the construction industry to anticipate and optimize the compressive strength of glass wool reinforced clay bricks. Furthermore, the findings contribute to advancing the understanding of these novel composite materials, fostering sustainable and resilient construction practices.

Keywords: Artificial Neural Networks (ANN), compressive strength, glass wool, reinforced brick, construction practices.

1 Introduction

In the realm of sustainable construction materials, the integration of novel components holds promise for enhancing structural performance and environmental viability. Among these innovations, the utilization of glass wool in reinforcing traditional clay bricks has emerged as a compelling avenue. This study focuses on harnessing the power of Artificial Neural

Networks (ANN) to forecast the compressive strength of glass wool reinforced clay bricks. By amalgamating experimental data and machine learning techniques, this research endeavors to establish a predictive model capable of accurately estimating the strength of these composite materials. The exploration of ANN-based predictive capabilities stands to revolutionize the construction industry by offering a reliable methodology for optimizing material compositions and structural resilience in glass wool reinforced clay bricks. The assessment of building materials, particularly the evaluation of compressive strength, holds paramount importance. However, the experimental determination of concrete's compressive strength within a laboratory setting is an intricate, time-consuming process, constrained by limited testing parameters. Despite exhaustive efforts in labs, exploring the myriad composition combinations remains impractical. The prediction of compressive strength stands pivotal in ensuring the structural safety and reliability of constructions. Over recent decades, extensive research has focused on mathematical modeling as a potent tool for this purpose. This comprehensive literature review examines diverse mathematical modeling approaches aimed at predicting compressive strength.

Artificial Neural Networks (ANN) demonstrate effectiveness in capturing diverse attributes of concrete, encompassing its mechanical properties such as compressive and tensile strength, slump, filling capacity, and segregation. ANN proves applicable across various concrete compositions and types, Naderpour and Mirrashid, (2018), Saridemir (2009) and Sobhani et al. (2010).

Ray et al. conducted a study examining the effects of incorporating fine glass aggregate and condensed milk can fiber (Sn) on compressive and splitting tensile strength at three different curing ages, employing an Artificial Neural Network (ANN). Their findings demonstrated a high level of accuracy, emphasizing the efficacy of machine learning technology in forecasting concrete properties, as noted by Yesilmen and Tatar (2022) and Almasaeid et al. (2022). Earlier investigations in the early 2000s by Yang et al. (2003) and Kim and Kim (2002) underscored the significant potential of optimizing mix proportioning and predicting concrete properties. Apostolopoulou et al. (2020) explored the use of ANNs to simulate the characteristics of lime-based mortars, including compressive and flexural strength, and consistency, with resulting ANN models showing satisfactory alignment with experimental data. In a recent study, Gupta et al. (2019) employed an ANN due to the absence of a mathematical model for swiftly predicting mechanical properties in rubberized concrete. The trained network, informed by recent research data, effectively predicted compressive strength, modulus of elasticity (both static and dynamic), and mass loss. Similar conclusions were drawn in various other studies on this type of concrete, with some focusing on predicting the properties of recycled aggregate-based concrete, as observed by Mhaya et al. (2021). Artificial Neural Networks (ANNs), integral to the realm of machine learning, employ mathematical techniques centered on interconnected layers of nodes, DeRousseau et al. (2018). An ANN, as part of artificial intelligence, is designed to tackle intricate problems and phenomena through a system that mimics the interconnected structure of biological neural networks. While bearing some resemblance to traditional digital computing, ANNs possess additional advantages such as equivalent processing modes, distributed information storage, and high accuracy. They exhibit robustness post-training and adaptability to new information and learning, Agrawal and Sharma (2010).

The architecture of an ANN typically consists of an input layer of neurons, with subsequent layers embedded within. These neurons contribute to predicting process outcomes, and the interconnection between layers relies on link weights, Rafir et al. (2001). In essence, an ANN is a computing system comprising multiple interconnected processing elements that dynamically analyze information in response to external inputs. The network excels in memorizing data characteristics and can establish connections between new and existing data with varying degrees of success, Flood and Kartam (1994). The hidden layers (HLs) act as connectors or information carriers, enabling the network to extract non-linear correlations from the provided dataset, Sadrmomtazi et al. (2013).

Ahmad et al. (2023) introduced predictive models in their research, specifically targeting concrete compressive strength and considering the role of waste glass aggregates for partial substitutes for sand. Examining 145 data points from prior studies, they developed models such as linear, non-linear regression, and an ANN model. These models integrated several influential factors such as time of curing, water/cement ratio, cement and fine aggregate, waste glass percentage, superplasticizer and coarse aggregate and silica fume. Evaluation techniques included several mean error techniques, Scatter Index, and the coefficient of determination. The findings highlighted the superiority of the Artificial Neural Network model in predicting compressive strength within standard concrete blends incorporating varying amounts of waste glass aggregates.
However, it's imperative to note that these models are specifically tailored to forecast compressive strength in standard concrete blends featuring varying compositions of waste glass aggregates. Their applicability beyond this specific context might require further validation and adjustments to accommodate different material variations and conditions.
Emadaldin Mohammadi Golafshani et al. (2020) hybridized Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) with Grey Wolf Optimizer (GWO) to predict concrete compressive strength. Data from 2817 records were used to develop six ANN and three ANFIS models. GWO integration improved training and generalization for both ANN and ANFIS. ANN with Levenberg-Marquardt algorithm outperformed other models and all ANFIS models. Achieving reliable predictions saves time, energy, cost, and aids in construction scheduling and framework removal decisions. The hybridized models offer an efficient means for accurate compressive strength predictions. This approach contributes to improved construction practices and informed decision-making.
Ahmed, H.U. et al. (2023) delved into an extensive exploration of machine learning techniques, encompassing artificial neural network (ANN), multi-expression programming, full quadratic, linear regression, and M5P-tree, aiming to forecast the compressive strength (CS) of geopolymer concrete (GPC). Leveraging approximately 207 CS data points sourced from literature, they established and refined models. Eleven pertinent input parameters and one output variable shaped the modeling process. The models underwent rigorous assessment using four statistical indicators, accompanied by a sensitivity analysis. Impressively, the ANN model emerged as the most precise in determining GPC CS, revealing noteworthy influences from variables like alkaline solution-to-binder ratio, molarity, NaOH content, curing temperature, and concrete age.

Meanwhile, in a separate study, Ali Kaveh and Neda Khavaninzadeh (2023) undertook a comprehensive investigation focusing on refining feed forward backpropagation (FFB) and radial basis function (RBF) neural networks to anticipate fiber reinforced polymer (FRP) strength. To enhance their accuracy, they integrated meta-heuristic algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Colliding Bodies Optimization (CBO), and Enhanced Colliding Bodies Optimization (ECBO) into ANNs. The study utilized data extracted from 223 Carbon FRP (CFRP) tests, considering parameters such as concrete compressive strength, sample geometry, fiber elastic modulus, thickness, and strength. Validation metrics encompassed mean square error, root mean square error, and correlation coefficient (R). Impressively, the ECBO algorithm showcased superior performance, particularly when coupled with FFB neural networks, demonstrating reduced error rates and

heightened precision compared to RBF models. This amalgamation proved highly effective, illustrating improved accuracy in predictions.
Ahmad SA et al. (2023) addressed the sustainability challenges in concrete and mortar production due to their heavy resource consumption. Waste materials, like waste glass, have gained attention as potential cement replacements in concrete to mitigate environmental and economic concerns in the construction industry. The study collected 153 data points from previous research and developed three predictive models (linear regression, nonlinear regression, and ANN) for compressive strength using variables like curing time, w/b ratio, cement, sand, waste glass, and coarse aggregate content. Statistical assessments (RMSE, MAE, Scatter Index, and R2) were used to evaluate model efficiency. The ANN model outperformed others in predicting compressive strength of normal concrete mixes with waste glass powder.
Ghafor K et al. (2022) proposed alternative models artificial neural network (ANN), nonlinear model (NLR), nonlinear model (LR), multi-logistic model (MLR), (M5P) to estimate engineered cementitious composites (ECC) compressive strength with fly ash. Data from 205 mixes with various proportions, fiber characteristics, and curing durations were used for modeling. Statistical evaluations favored the ANN model.
Nagaveni Thallapalli and S V S N D L Prasanna (2022) researched on the influence of Local climatic conditions on Solar Radiation (SR) reaching Earth's surface. In India, ample SR is received, crucial for energy and climate studies. Meteorological data from Hyderabad (2009-2020) was employed, including Max. Temp. (Tmax), Min. Temp. (Tmin), Mean Air Temp. (Tmean), Sunshine hours (n), and Relative Humidity (RH). Conventional equations (Abdalla, Angstrom) and data-driven models (ANN, MGGP) estimated SR. Model equations utilized parameters from each conventional equation. Results indicated favorable SR estimation and simplification of testing data. R2 values are 0.976 (training) and 0.964 (testing). MGGP and ANN models demonstrated efficiency, reliability, and accurate prediction for 2021, aligned with analytical results from established equations.
Ali Danandeh Mehr et al. (2020) introduced the Multiple Genetic Programming (MGP) technique, showcasing its prowess in significantly enhancing predictive accuracy when compared to the standalone Genetic Programming (GP). Their study focused on utilizing rainfall data collected from two distinct weather forecasting stations located within the Lake Urmia Basin in Iran. This detailed analysis was dedicated to demonstrating the MGP model's efficacy in forecasting 1-month rainfall patterns. Remarkably, the evaluation of their models revealed that the MGP technique outperformed traditional methods, displaying superior statistical performance at both weather stations.
In a separate but equally noteworthy study, Anurag Malik et al. (2020) conducted an in-depth investigation into various predictive models, including the Support Vector Machine (SVM), Multiple Model-Artificial Neural Network (MMANN), Multivariate Adaptive Regression Spline (MARS), Multi-Gene Genetic Programming (MGGP), and 'M5Tree.' Their primary objective revolved around estimating monthly pan evaporation (EPm) levels at stations situated in Ranichauri and Pantnagar, India. Employing the Gamma test, they meticulously identified the most influential input variables for these five diverse models. The results notably highlighted the efficiency and reliability of the MM-ANN-1 and MGGP-1 models in aiding local stakeholders with effective water resource management strategies tailored to their specific needs and geographical locations. This finding underlined the potential impact of these models on facilitating sustainable water resource utilization and conservation practices within the region.
Garg et al. (2013) introduced a novel simulation approach known as Multi Gene-genetic Programming (MGGP) to investigate the complex relationship between water content and two crucial input parameters: soil suction and volumetric crop root content. The proposed

methodology utilizes a stepwise regression technique, which is grounded in statistical principles, to model and analyze this intricate interaction. Through this innovative approach, the researchers aimed to unravel the intricate dynamics of water content variation by considering the interplay between soil suction and volumetric crop root content, thus contributing to a deeper understanding of soil-water dynamics in agricultural and environmental contexts.

2 Methodology

In this study, the MATLAB software's ANN Tool was utilized to determine the most effective Glass Wool replacement in Clay bricks. The methodology employed, illustrated in Figure 1, involved comparing and assessing the results obtained from modeling the impact of 4% Glass Wool replacement in clay. The analysis integrated Glass Wool percentage, Temperature, Load, and Area as input parameters, while compressive strength served as the output parameter for the ANN model. This model underwent two distinct phases: training (calibration) and testing (validation). During the training phase, 128 data points were used to train the network, reserving 8 data points for the testing phase. The objective was to attain an optimal solution, gauged by metrics such as mean squared error (MSE) and Correlation coefficient (R). Table 1 outlines the specific values and parameters embedded within the model. The training phase concluded once the mean squared error (MSE) during the testing phase reached negligible levels.

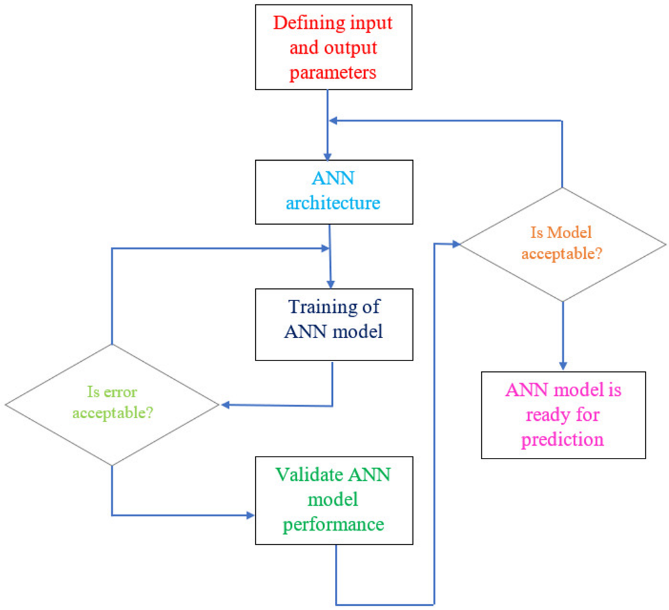


Fig.1 ANN Methodology

The ANN structure was tested for different number of neurons and combination that suits the best are considered. The number of neurons in the model is 20 and hidden layers is 2. The ANN model was optimal at 1000 iterations and 2 hidden layers.

Table 1. Parameters Used in the Model

Parameter(s)	ANN
Number of input layers	4
Number of hidden layers	2
Number of neurons in hidden layers	20
Training function	TRAINLM
Adoption learning function	LEARNGDM
Performance Function	MSE, MSEREG, SSE
Testing Function	TRANSG
Learning Function	1000 epochs

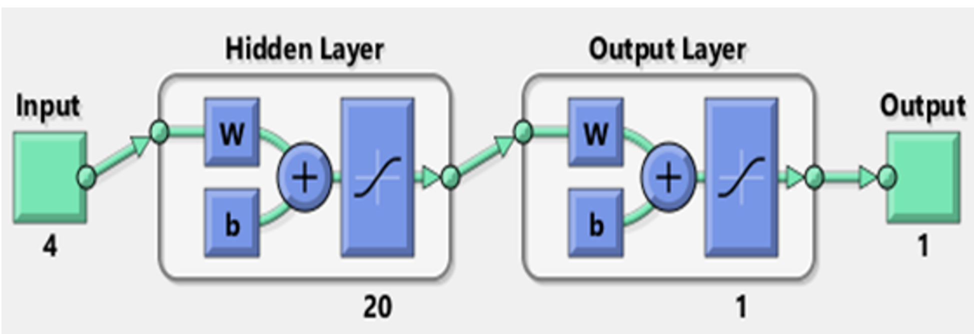


Fig. 2 Model Network

The input parameters considered for the study are percentage of glass wool replacement, temperature, load and area. The output is the compressive strength. By changing of the number of hidden layers there in no significant change in the R value. The R value is obtained around 0.99. By changing the number of Iterations there is significant change in R value, but the change is also significant up to a certain limit. In further increase in the number of iterations from 1000 to 2000 and to 4000, significant change was not observed in R value. Different performance functions viz., MSE, MSEREG, SSE were adopted for evaluation of training data.
The model analysis was extended in predicting the compressive strength for 4% replacement of Glass Wool. Further, the ANN values obtained were also compared with experimental results for 4% Glass Wool replacement.

3 Results and Discussions

Training R values for performance functions viz. MSE, MSEREG and SSE are indicated in table 2.
The compressive strength of bricks for 4% was predicted and was found that the error percentage is insignificant and tabulated in Table 3.

Table 2. Training R Values

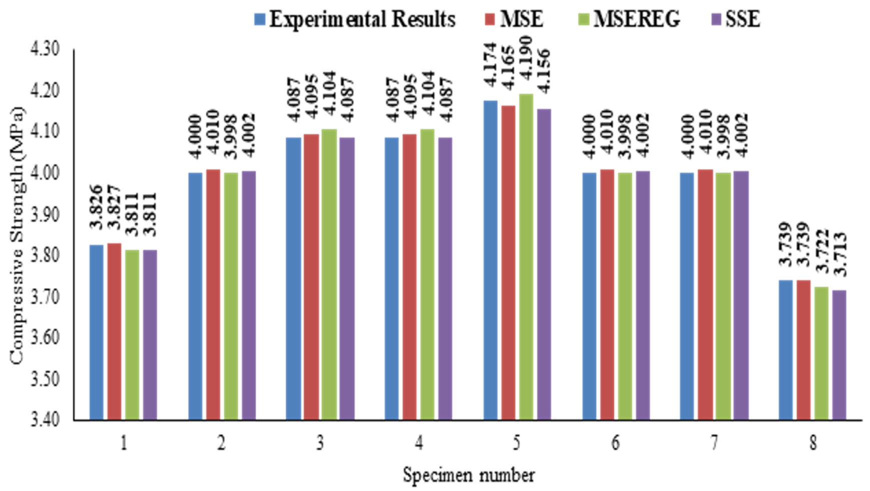
Performance Function	Training R value
MSE	0.99999
MSEREG	0.99998
SSE	1

Table 3. Predicted Values of Compressive Strength for 4% replacement

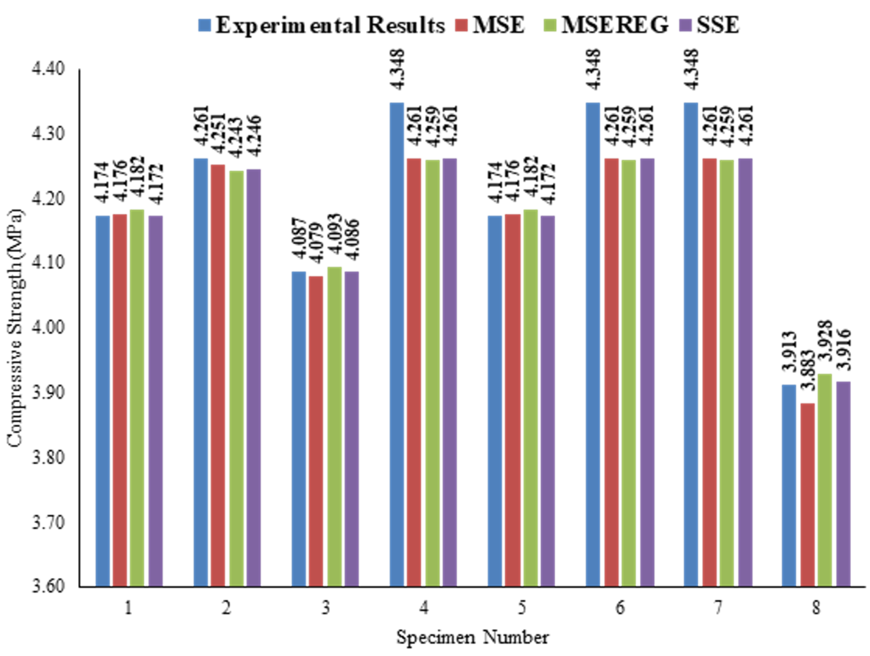
Temperature (°C)	MSE	MSEREG	SSE
750	3.827	3.811	3.811
	4.010	3.998	4.002
	4.095	4.104	4.087
	4.095	4.104	4.087
	4.165	4.190	4.156
	4.010	3.998	4.002
	4.010	3.998	4.002
	3.739	3.722	3.713
1000	4.176	4.182	4.172
	4.251	4.243	4.246
	4.079	4.093	4.086
	4.261	4.259	4.261
	4.176	4.182	4.172
	4.261	4.259	4.261
	4.261	4.259	4.261
	3.883	3.928	3.916

The ANN predicted values for 4% replacement of Glass Wool were further compared for all three performance functions with the experimental results for 750°C and 1000°C as highlighted in Figure 3.

 https://doi.org/10.1051/e3sconf/202455904006



(a) 750°C



(b) 1000°C

Fig. 3. Experimental results

The average values of compressive strength for 4% replacement were found to be 3.993 MPa, 3.990 MPa, 3.982 MPa and 3.989 MPa for MSE, MSEREG, SSE and experimental results respectively for 750oC. For 1000oC the compressive strength values were 4.168 MPa, 4.175 MPa, 4.172 MPa and 4.207 MPa in the same order.

4 Conclusion

Mathematical modeling was conducted to reinforce and verify experimental findings concerning compressive strength, employing ANN for partial replacements ranging from 0% to 3.5%. Furthermore, the ANN was utilized to forecast compressive strength specifically for a 4% replacement scenario, yielding prediction errors measured through MSE, MSEREG, and SSE at 0.1003%, 0.0251%, and 0.1755%, respectively, in comparison to the experimental results.

References

1. Ahmad, S.A., Ahmed, H.U., Ahmed, D.A. et al. (2023). "Predicting concrete strength with waste glass using statistical evaluations, neural networks, and linear/nonlinear models". Asian J Civ Eng. https://doi.org/10.1007/s42107-023-00692-4.
2. Ahmad, S.A., Rafiq, S.K., Ahmed, H.U. et al. (2023). "Innovative soft computing techniques including artificial neural network and nonlinear regression models to predict the compressive strength of environmentally friendly concrete incorporating waste glass powder". Innov. Infrastruct. Solut., 8(119). https://doi.org/10.1007/s41062-023-01089-7.
3. Ahmed, H.U., Mohammed, A.S., Faraj, R.H. et al. (2023). "Innovative modeling techniques including MEP, ANN and FQ to forecast the compressive strength of geopolymer concrete modified with nanoparticles". Neural Comput & Applic, 35, 12453–12479. https://doi.org/10.1007/s00521-023-08378-3.
4. Ali Kaveh, Neda Khavaninzadeh. (2023). "Efficient training of two ANNs using four meta-heuristic algorithms for predicting the FRP strength". Structures, Volume 52, Pages 256-272. https://doi.org/10.1016/j.istruc.2023.03.178.
5. Emadaldin Mohammadi Golafshani, Ali Behnood, Mehrdad Arashpour. (2020). "Predicting the compressive strength of normal and High-Performance Concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer". Construction and Building Materials, Vol. 232, 117266. https://doi.org/10.1016/j.conbuildmat.2019.117266.
6. Fatih Özcan, Cengiz D. Atiş, Okan Karahan, Erdal Uncuoğlu, Harun Tanyildizi. (2009). "Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete". Advances in Engineering Software, Volume 40, Issue 9, Pages 856-863. https://doi.org/10.1016/j.advengsoft.2009.01.005.
7. Ghafor K, Ahmed HU, Faraj RH, Mohammed AS, Kurda R, Qadir WS, Mahmood W, Abdalla AA. (2022). "Computing Models to Predict the Compressive Strength of Engineered Cementitious Composites (ECC) at Various Mix Proportions". Sustainability, 14(19), 12876. https://doi.org/10.3390/su141912876.
8. Naderpour, H.; Mirrashid, M. An innovative approach for compressive strength estimation of mortars having calcium inosilicate minerals. J. Build. Eng. 2018, 19, 205–215.
9. Sarıdemir, M. Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks. Adv. Eng. Softw. 2009, 40, 350–355. [CrossRef]
10. Sobhani, J.; Najimi, M.; Pourkhorshidi, A.R.; Parhizkar, T. Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models. Constr. Build. Mater. 2010, 24, 709–718.
11. Mhaya, A.M.; Huseien, G.F.; Faridmehr, I.; Abidin, A.R.Z.; Alyousef, R.; Ismail, M. Evaluating mechanical properties and impact resistance of modified concrete

containing ground Blast Furnace slag and discarded rubber tire crumbs. Constr. Build. Mater. 2021,295, 123603.
12. Ray, S.; Haque, M.; Ahmed, T.; Nahin, T.T. Comparison of artificial neural network (ANN) and response surface methodology (RSM) in predicting the compressive and splitting tensile strength of concrete prepared with glass waste and tin (Sn) can fiber. J.King Saud Univ. Eng. Sci. 2021, 4, 144–169.
13. Yesilmen, S.; Tatar, B. Efficiency of convolutional neural networks (CNN) based image classification for monitoring construction related activities: A case study on aggregate mining for concrete production. Case Stud. Constr. Mater. 2022, 17, e01372.
14. Almasaeid, H.H.; Suleiman, A.; Alawneh, R. Assessment of high-temperature damaged concrete using non-destructive tests and artificial neural network modelling. Case Stud. Constr. Mater. 2022, 16, e01080.
15. Yang, D.S.; Park, S.K.; Lee, J.H. A prediction on mix proportion factor and strength of concrete using neural network. KSCE J. Civ. Eng. 2003, 7, 525–536.
16. Kim, J.I.; Kim, D.K. Application of neural networks for estimation of concrete strength. KSCE J. Civ. Eng. 2002, 6, 429–438.
17. Apostolopoulou, M.; Asteris, P.G.; Armaghani, D.J.; Douvika, M.G.; Lourenço, P.B.; Cavaleri, L.; Bakolas, A.; Moropoulou, A. Mapping and holistic design of natural hydraulic lime mortars. Cem. Concr. Res. 2020, 136, 106167.
18. Gupta, T.; Patel, K.; Siddique, S.; Sharma, R.K.; Chaudhary, S. Prediction of mechanical properties of rubberised concrete exposed to elevated temperature using ANN. Measurement 2019, 147, 106870.
19. DeRousseau, M.; Kasprzyk, J.; Srubar,W. Computational design optimization of concrete mixtures: A review. Cem. Concr. Res. 2018, 109, 42–53.
20. Agrawal, V.; Sharma, A. Prediction-of-Slump-in-Concrete-using-Artificial-Neural-Networks. World Acad. Sci. Eng. Technol. 2010,4, 279–286.
21. Rafiq, M.; Bugmann, G.; Easterbrook, D. Neural network design for engineering applications. Comput. Struct. 2001, 79, 1541–1552.
22. Flood, I.; Kartam, N. Neural Networks in Civil Engineering. I: Principles and Understanding. J. Comput. Civ. Eng. 1994, 8, 131–148.
23. Sadrmomtazi, A.; Sobhani, J.; Mirgozar, M. Modeling compressive strength of EPS lightweight concrete using regression, neural network and ANFIS. Constr. Build. Mater. 2013, 42, 205–216.